We build a new empirical framework for analyzing destination-specific markup and quantity adjustments by exporters. Our first contribution is an unbiased estimator of the destination-specific markup elasticity to the exchange rate that isolates marginal costs in large unbalanced panels where the set of markets served by a firm varies endogenously with currency movements. Relatedly, we estimate firms' cross-market supply elasticity-defined as the adjustment in relative quantities across markets associated to exchange rate-induced adjustment in markups. Our second contribution is a new classification of Harmonized System products into high and low differentiation goods which we used as a proxy for exporters' market power. Exploiting information about Chinese “measure words” reported in customs declarations, we add value to existing classification systems including Rauch (1999) and the UN's Broad Economic Categories. Applying this framework to exporters from China, we find that the average markup elasticity is higher for high differentiation goods (20%) than for low differentiation goods (6%). The cross-market supply elasticities are correspondingly lower for high than low differentiation goods, 0.83 and 2.47, respectively. Finally, we discuss how our estimated elasticities can serve as a diagnostic tool to guide the development of open macro models.
Abstract

We build a new empirical framework for analyzing destination-specific markup and quantity adjustments by exporters. Our first contribution is an unbiased estimator of the destination-specific markup elasticity to the exchange rate that isolates marginal costs in large unbalanced panels where the set of markets served by a firm varies endogenously with currency movements. Relatedly, we estimate firms’ cross-market supply elasticity—defined as the adjustment in relative quantities across markets associated to exchange rate-induced adjustment in markups. Our second contribution is a new classification of Harmonized System products into high and low differentiation goods—which we used as a proxy for exporters’ market power. Exploiting information about Chinese “measure words” reported in customs declarations, we add value to existing classification systems including Rauch (1999) and the UN’s Broad Economic Categories. Applying this framework to exporters from China, we find that the average markup elasticity is higher for high differentiation goods (20%) than for low differentiation goods (6%). The cross-market supply elasticities are correspondingly lower for high than low differentiation goods, 0.83 and 2.47, respectively. Finally, we discuss how our estimated elasticities can serve as a diagnostic tool to guide the development of open macro models.

JEL classification: F31, F41

Keywords: exchange rates, pricing-to-market, product classification, differentiated goods, markup elasticity, trade elasticity, China.
Disclaimer: HM Revenue & Customs (HMRC) agrees that the figures and descriptions of results in the attached document may be published. This does not imply HMRC’s acceptance of the validity of the methods used to obtain these figures, or of any analysis of the results. This work contains statistical data from HMRC which is Crown Copyright. The research datasets used may not exactly reproduce HMRC aggregates. The use of HMRC statistical data in this work does not imply the endorsement of HMRC in relation to the interpretation or analysis of the information.

We thank Andy Atkeson, Andy Bernard, Ariel Burstein, Natalie Chen, Oleg Itskhoki, Thierry Mayer, our discussants Doireann Fitzgerald, Leonardo Melosi, Jakob Munch and Zhihong Yu, and participants at the Empirical Investigations in Trade and Investment Conference (Tokyo), March 2018; the Annual GEP/CEPR Postgraduate Conference, April 2018; the Rocky Mountain Empirical Trade Conference (Ottawa), May 2018; the China Finance Review International Conference (Shanghai), June 2018; the “New Issues in Macroeconomics” Conference (Ischia, Italy), June 2018; the Barcelona GSE Summer Forum, June 2018; the 2018 Tsinghua Workshop in International Finance (Beijing), June 2018; the California Trade Workshop (San Luis Obispo, California), June 2018; the NBER Summer Institute Conference on International Finance and Macro; and participants in seminars at the University of Southern California, the Fed Board, and the University of Oregon, for comments. We are also grateful to those who offered feedback on preliminary versions presented at the Paris Trade Seminar, March 2017; the China Center for Economic Research at Peking University’s Summer Institute (Yantai, China), June 2016; the Banque de France, December 2015; and the European Trade Study Group (Paris), September 2015.

We thank Cambridge INET, the Centre For Macroeconomics, and the Economic and Social Research Council (United Kingdom) for supporting our research. We thank the staff of the HMRC datalab, especially Yee-Wan Yau, for supporting us in our analysis of UK administrative data.
1 Introduction

A fundamental feature of international goods markets is that firms exporting to more than one destination account for the lion’s share of cross-border trade. Serving multiple markets, these firms face demand conditions and market structures that differ across locations and are inherently time-varying. Indeed, global and local shocks to fundamentals, as well as country-specific economic policies, bear upon how much competition exporters endure from local and other international producers. Effectively, from the perspective of an exporter, a changing local economic environment systematically creates opportunities to raise profits, or induces the need to contain losses, through destination-specific adjustment of export prices, i.e., by engaging in pricing-to-market (Krugman (1986) and Dornbusch (1987)).

While global and local shocks naturally lead firms to reconsider their pricing strategies, their choice sets are not unconstrained, but crucially reflect the extent to which firms have power in local markets and can keep the foreign markets for their products segmented to minimize arbitrage. For example, an exporting firm must consider not only the direct effect of changes in the value of its own currency on own competitiveness, but also the response of foreign rivals to swings in the bilateral exchange rates between destination markets and third countries—as this has key implications for the firm’s residual demand and, hence, local pricing power. In this sense, a multilateral analysis of markup and quantity elasticities can provide fundamental insight on the effective degree of competition within and across markets, especially if articulated by product and firm characteristics.

Trade globalization has heightened the importance of understanding the many factors that drive a global firm’s pricing strategy. Of course, pricing-to-market is already a standard feature in open macro models, increasingly featuring firm dynamics and competition (see, e.g., Bergin and Feenstra (2001) and Atkeson and Burstein (2008)), vertical interactions of exporters with local producers and distributors (see, e.g., Corsetti and Dedola (2005)), and nominal rigidities in either local or a (third-country) vehicle currency (Corsetti, Dedola and Leduc (2008), Gopinath (2015) and Casas, Diez, Gopinath and Gourinchas (2017)).1 By the same token, the increasing availability of high-dimensional administrative customs databases has already been providing a wealth of new insights about the pricing behaviour of firms (see, e.g., Berman, Martin and Mayer (2012), Chatterjee, Dix-Carneiro and Vichyanond (2013), Amiti, Itskhoki and Konings (2014), Fitzgerald and Haller (2014), De Loecker, Goldberg, Khandelwal and Pavcnik (2016), Fitzgerald and Haller (2018)). However, there is a sense in which research has yet to fully exploit the data in all its dimensions—and in ways that can inform our understanding and modelling of multilateral

1Leading questions to address range from imported inflation and the consequences of large depreciations to efficiency losses from currency misalignments and the design of stabilization policy in an open economy (Engel (2011) and Corsetti, Dedola and Leduc (2018)).
competition by exporters in local and global markets.

In this paper, we build an empirical framework suitable for analyzing the local or destination-specific markup and quantity adjustments of multi-destination exporters in firm and product-level administrative datasets.\(^2\)

On methodological grounds, our contribution is threefold. First, we construct an estimator of the markup elasticity to the exchange rate that exploits multiple destination-specific prices of individual products in order to net out changes in unobserved marginal costs—that we dub the Trade Pattern Sequential Fixed Effects (TPSFE) estimator. The general approach builds on the seminal work by Knetter (1989). However, unlike Knetter’s original method, our estimator is free of the bias introduced when firms endogenously discontinue or open destination markets in response to exchange rate fluctuations—implying that the panel of observations is endogenously unbalanced (Han (2017)). We derive a identification condition stating the assumptions required for our proposed TPSFE estimator to be unbiased—a condition that is weaker than typically imposed in the pricing-to-market literature.

Second, we show how to estimate the market-specific responsiveness of quantities to currency fluctuations. We propose a two-stage procedure. In the first stage, we estimate the predicted changes in relative markups that stem from movements in relative exchange rates using our TPSFE estimator; in the second stage, we regress changes in relative quantities across destinations on the predicted relative markup changes and other aggregate control variables conditional on the firm and product-level trade patterns.\(^3\) As our estimator differences out common supply factors, the second stage measures the degree to which the quantity supplied responds to shifts in relative demand across destinations due to changes in relative markups (which, in turn, arise from differences in local factors). We refer to this measure as the within-firm cross market supply elasticity (CMSE). This is developed for highly-disaggregated data along the lines of work by Feenstra (1994) and Broda and Weinstein (2006), estimating import demand and export supply elasticities. The elasticity is similar to the cross-destination trade value response to tariffs in Bown and Crowley (2007), but introduces

---

\(^2\)Our framework has been specifically developed for application to large, four-dimensional (firm-product-destination-time) unbalanced customs databases which cover the universe of firm and product level export records for a country. Recent papers (Berman, Martin and Mayer (2012), Amiti, Itskhoiki and Konings (2014), and De Loecker, Goldberg, Khandelwal and Pavcnik (2016)) have proposed different methodologies aimed at identifying marginal costs and markups, using detailed information on production and costs, including prices and costs of domestic and imported inputs. An advantage of these methodologies over our analysis is that they provide estimates of the overall level of markups. An advantage specific to our methodology, however, is a much lower data requirement and a larger range of applicability to standard customs datasets. We obviously see strong complementarities and high potential gains from combining methodologies and cross checking results.

\(^3\)The conventional approach to investigate quantity responses to exchange rates, as taken for example by Berman, Martin and Mayer (2012), directly regresses quantities on exchange rates. Apart from the difficulty in controlling the marginal cost, the conventional method would in general underestimate the heterogeneity in quantity responses across products and firms. This arises from the duality property of markup responses—a high markup elasticity often originates from a market structure with low substitutability that is associated with a low quantity response.
a new identification strategy. Our CMSE elasticity potentially provides an alternative measure of market power in a multi-country context that compliments empirical studies characterizing the relationship between market share and optimal exchange rate pass through, e.g., Feenstra, Gagnon and Knetter (1996) and Auer and Schoenle (2016).

Taken together, these two elasticities, the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) offer insights into the empirical relevance of local market structures for globally engaged firms.

However, the intensity of competition among firms varies not only with local market structure, but also systematically across different types of globally-traded products—producers of highly differentiated manufactured goods hold more pricing power than producers of undifferentiated commodities. Our third methodological contribution is a novel product classification of traded goods into categories of market power, or, equivalently, the degree of product differentiation. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product’s quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on “measure words” recorded in the Chinese Customs Database to construct a general product classification for the Harmonized System.

Our classification improves the popular classification by Rauch (1999) in two ways. First, and most importantly, we break down Rauch’s large class of differentiated manufactured goods into two similarly-sized groups, distinguishing high and low differentiation products. Applying Rauch (1999)’s categories, we find about 80 percent of Chinese exports (observation weighted) are classified as differentiated. According to our Corsetti-Crowley-Han-Song (CCHS) linguistics-based classification, about half of these, amounting to 39 percent of all Chinese exports, are actually highly differentiated, while 41 percent exhibit low differentiation. Second, many products that are left unclassified by Rauch can be classified as high or low differentiation goods according to CCHS.

On empirical grounds, we apply our methodology to multi-destination exporters from China using annual data on firm-product-destination exports over 2000-2014. This period includes both the last years of the dollar-peg regime (2000-2005) and the early years of the more relaxed managed float (2006-2014). The invoicing currency of Chinese exports is not recorded in our dataset, but the US dollar is widely-held to have been the principal invoicing currency for Chinese exports throughout this period.

---

4 The database consists of monthly records by firm-product-destination for 2000-2006 and annual records by firm-product-destination for 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in our analysis.

5 See appendix D.3 for evidence on dollar invoicing.
regimes during our sample period, we exclude exports to the US in order to obtain a comparable sample of countries over the full sample period. After merging available macroeconomic data and eliminating single-destination and single-year exporters, the sample consists of over 200,000 multi-destination exporters, around 8,100 HS08 products, and 154 foreign markets over 15 years. We implement our TPSFE estimator conditional on price changes; our results are therefore fully comparable with recent estimates of exchange rate pass through (ERPT) derived using the approach of Gopinath, Itskhoki and Rigobon (2010) and estimates of markup elasticities by Fitzgerald and Haller (2014).

Our main empirical findings are as follows. First, the destination-specific markup elasticity is moderate, especially for high differentiation products—suggesting that, on average, firms engage in significant pricing-to-market. Over 2006-2014 (after China gave up the dollar peg), our average estimate for high differentiation goods is as high as 20%, and peaks at 32% for consumption goods characterized by high differentiation. On average, for high differentiation goods, around two-thirds of a firm’s export price adjustment to the exchange rate is due to a destination-specific markup adjustment. Conversely, our estimates of the markup elasticity are small and close to zero for products that we classify as low differentiation goods—a result that validates our linguistics-based product classification. For low differentiation goods, firms appear to charge a common reference price to customers in all destination markets.

Second, we show that destination-specific markup adjustments motivated by exchange rate movements actually translate into differentiated quantity responses across markets. Applying our two-stage procedure, the difference in the cross-market supply elasticity between consumption goods and intermediates is substantial, 0.54 vs 2.92. When further disaggregated under the CCHS product classification, the gap between estimates opens to a chasm—the CMSE of high differentiation consumption goods, 0.23, suggests an extreme amount of market segmentation. The CMSE for low differentiation intermediates, 3.27, suggests something much closer to an integrated world market.

While the focus of this paper is mainly empirical, we should stress that our methodology is motivated and driven by open economy theory. In particular, our estimates of the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) have been designed to provide a novel diagnostic tool to guide and discipline the development of open-economy models. In ongoing work, we are developing a multi-country model with features drawn from leading contributions in the literature. At the end of the paper, we briefly summarize our results so far, which indeed suggest that our elasticities have revealed that different theoretical elements - espe-

---

6 We also omit exports to Hong Kong from our analysis because of the changing importance of its role as an entrepôt over time (see Feenstra and Hanson (2004)). Further, we treat the eurozone as a single economic entity and aggregate the trade flows (quantities and prices) to eurozone destinations at the firm-product-year level.
cially competition among producers of substitutes and vertical interactions between producers and distributors – are necessary to capture important aspects of observed behaviour.

The rest of the paper is organized as follows. Section 2 presents our empirical framework. Section 3 summarizes the database. Section 4 presents our empirical results. In section 5, we describe our ongoing work to build a multi-country general equilibrium theoretical framework to understand markup and quantity adjustments across markets. We calibrate this model to match and interpret the estimated destination-specific markup elasticities and cross-market supply elasticities. A brief section discusses the implications of our analysis for open-economy modeling. Section 6 concludes.

2 Empirical Framework

In this section, we introduce an empirical framework designed to study adjustments to markups and quantities of products sold by firms across multiple foreign markets. We first present our Trade Pattern Sequential Fixed Effect Estimator (TPSFE), suitable for estimating markup elasticities to changes in destination-specific conditions while controlling for unobserved product-level marginal cost within a firm in an environment with endogenous market selection. Second, we show how to use the logic of the TPSFE to construct an estimator of adjustmentst to quantities sold in response to changes in relative market conditions; this estimator sheds new light on how destination-specific markup adjustments translate into changes in quantities sold across markets. Lastly, we describe a new classification for Harmonized System products which distinguishes between high and low differentiation goods and thus serves as a useful proxy for firms’ market power.

2.1 Estimating a markup elasticity with a large customs database

A typical customs database records information on export values and quantities that varies along at least four dimensions: product, firm, foreign destination, and time. Let $p_{ifdt}$ denote the logarithm of the price (approximated by the unit value) of good $i$, produced by firm $f$ and sold in destination $d$ in year $t$. The optimal price $p_{ifdt}$ can always be decomposed into a markup component, $\mu_{ifdt}$, and a marginal cost component $mc_{ifdt}$:

$$p_{ifdt} = \mu_{ifdt} + mc_{ifdt} \quad (1)$$

In appendix B.1, we show how the optimal price of a firm under any (static) pricing problem can always be decomposed into a markup component solely explained by the demand elasticity with respect to price and a marginal cost component.
where all the terms above are denominated in the exporter’s currency. The key question motivating our analysis is how to assess the response of the firm’s product markup in a destination market to a change in the local market condition measured by $e_{dt}$\textsuperscript{8}, that is:

$$\frac{\partial \mu_{itd}}{\partial e_{dt}} = \frac{\partial p_{itd}}{\partial e_{dt}} - \frac{\partial mc_{itd}}{\partial e_{dt}}$$ \hfill (2)

A major obstacle in obtaining markup elasticities, is that the marginal cost is unobserved and is highly likely to be correlated with $e_{dt}$ directly through imported inputs (see e.g., Amiti, Itskhoki and Konings (2014)) or indirectly, due to general equilibrium movements in the prices of factors of production (e.g., wages) and marginal costs.\textsuperscript{9} This obviously creates a daunting challenge for empirical analyses.\textsuperscript{10}

In principle, one could approach our question by constructing an estimate of marginal costs—a step that would require detailed firm-level information in conjunction with the customs dataset. Using balance sheet data, leading contributions have estimated productivity and marginal cost at the firm level [e.g., Berman, Martin and Mayer (2012) and Amiti, Itskhoki and Konings (2014)]. In relation to our question of interest, however, following this approach would confront us with a key issue. Even if we could obtain data on firms, information on production inputs would generally be available at the firm level—not at the firm-product level.\textsuperscript{11} Without some assumptions on how inputs are allocated across products and destinations, it would not be possible to estimate marginal cost at the firm-product-destination level. By way of example, the seminal contribution by De Loecker, Goldberg, Khandelwal and Pavcnik (2016) estimates firm-product level marginal costs and markups under the assumption that the production functions of single-product firms are representative of those of multi-product firms.

An alternative approach—with a much lower data requirement, i.e., relying exclusively on customs data—consists of exploiting variation across destination markets, in the spirit of Knitter (1989).\textsuperscript{12} Exploiting the fact that most firms sell each of their products to multiple destinations,

\textsuperscript{8}Throughout our analysis, we will focus on (differences in) movements of bilateral exchange rates across destination markets as the main source of variation. Nonetheless, our framework can be applied to study markup and quantity adjustments more generally, conditional on identified shocks to a variety of economic and policy disturbances, including changes in trade costs and tariffs.

\textsuperscript{9}For example, a positive home productivity shock that lowers the marginal cost of home producers may also appreciate the home currency against its trade partners.

\textsuperscript{10}See Goldberg and Knetter (1997) and Corsetti, Dedola and Leduc (2008) for a discussion. Analysis of exchange rate pass through and deviations from the Law of One Price has been the focus of an extensive literature including Engel and Rogers (1996), Crucini and Shintani (2008), and Cavallo, Neiman and Rigobon (2014).

\textsuperscript{11}We should stress that, in most countries, the mapping between customs databases and industrial-survey data is often incomplete, raising issues of sample selection. In addition, balance sheet data means information is only available at annual frequencies, making it impossible to carry out the analysis at a higher frequency (monthly or quarterly).

\textsuperscript{12}Knitter (1989) studies responses of product level price indices to exchange rates. To control for product level marginal cost, this author adds destination fixed effects—a methodology that is suitable if the panel of observations
one can obtain an estimator that controls for changes in the unobservable product-level marginal
cost within a firm over time by taking differences of prices across destination markets. Intuitively,
we write the components of the price for product \( i \) sold by a firm in a destination in terms of the
residual from the average of each component across destinations, as follows:

\[
\frac{\partial \mu_{ifdt}}{\partial e_{dt}} - \frac{1}{n_{if}^{D}} \sum_{d \in D_{if}} \frac{\partial \mu_{ifdt}}{\partial e_{d}} = \left[ \frac{\partial p_{ifdt}}{\partial e_{dt}} - \frac{1}{n_{if}^{D}} \sum_{d \in D_{if}} \frac{\partial p_{ifdt}}{\partial e_{d}} \right] - \left[ \frac{\partial \mu_{ifdt}}{\partial e_{dt}} - \frac{1}{n_{if}^{D}} \sum_{d \in D_{if}} \frac{\partial \mu_{ifdt}}{\partial e_{d}} \right] \tag{3}
\]

where \( n_{if}^{D} \) and \( D_{if} \) denote, respectively, the number and set of destination markets in which the
firm sells product \( i \) at time \( t \), with \( d_{if} \in D_{if} \). A challenge that arises in applying this differences-
across-destinations method to identifying destination-specific markups is that the set of destination
markets \( D_{if} \) at the firm-product level is not constant but can grow or shrink over time in response
to changes in local conditions.

Our contribution to this identification strategy is twofold. First, we address the market selection
problem in applying this identification strategy to highly disaggregated firm-product-destination
level datasets. Building on Han (2017), we propose a Trade Pattern Sequential Fixed Effect (TPSFE)
estimator that controls for possible endogenous selection of markets by conditioning estimates on the trade patterns of firms and products.

Second, we clarify what is required for identification in the presence of destination-specific
costs, if any exist, that could prevent the second term in brackets in equation (3) from being equal
to zero. We derive the identification condition and discuss the assumptions that are required for
identification strategies which exploit variation across destinations to produce unbiased estimates.
Moreover, we provide a structural interpretation of these required assumptions in appendix C.4.

### 2.1.1 Identification condition

We start by writing an expression for marginal costs that allows for the possibility that variation
depends not only on the firm and the product, but also on the destination:

\[
m_{ifdt} = \bar{m}_{if} + \psi_{ifdt} \tag{4}
\]

where

\[
\bar{m}_{if} = \frac{1}{n_{if}^{D}} \sum_{d \in D_{if}} m_{ifdt} \quad \text{and} \quad \psi_{ifdt} = m_{ifdt} - \bar{m}_{if}
\]

The first term, \( \bar{m}_{if} \), is the mean marginal cost, averaged across destinations for firm \( f \)’s prod-
is balanced, as is the case for industry-level price indices.
uct $i$ at time $t$ (denominated in the exporter’s currency). The second term, $ψ_{i\ell dt}$ captures any destination-specific components of marginal cost. More generally, as we observe unit values, this second term allows us to handle possible changes in the composition of varieties shipped under a particular product code to specific destinations. This possibility implies that $ψ_{i\ell dt}$ can be nonzero, even if the marginal cost of each variety has no destination-specific component.

The general condition for an estimator of the markup elasticity that exploits cross-destination variation to be unbiased is:

$$
\frac{1}{n^{DT}} \sum_d \sum_t (\bar{η}_{dt} - \bar{η}_d)(\bar{e}_{dt} - \bar{e}_d) = 0
$$

(5)

where $\bar{x}_j$ is the mean of variable $x$ taken over all dimensions other than $j$. $n^{DT}$ is the total number of destination-time periods. (For example, in a balanced panel, $n^{DT}$ is the number of destinations $n^D$ times the number of time periods $n^T$.) The term $(\bar{η}_{dt} - \bar{η}_d)$ measures the deviations of the average destination-specific marginal cost component across firms and products within a destination over time. The term $(\bar{e}_{dt} - \bar{e}_d)$ measures deviations of the bilateral exchange rate from its long-run mean over time.

The condition (5) is trivially satisfied if there is no destination-specific component to marginal costs. For example, $ψ_{i\ell dt} = 0$ if the goods sold to different destinations under the same product code are identical at the firm-product level. More crucially, however, the condition clarifies that the presence of destination-specific marginal costs does not automatically lead to a violation of identification. An important instance in which condition (5) is satisfied occurs when the cross-destination distribution of the destination-specific component does not change over time, e.g., high quality varieties of a product are consistently sold to rich destinations.

It is worth stressing that the above identification condition requires no assumption on firm and product idiosyncratic shocks, and is weaker than orthogonality of the destination-specific marginal cost component $ψ_{i\ell dt}$ and the bilateral exchange rate $e_{dt}$, a condition which has been emphasized in the literature on exchange rate pass through (see, e.g., Corsetti, Dedola and Leduc (2008)). Note that only the mean of the destination-specific marginal cost component across all firms and products, $\bar{ψ}_{dt}$, enters the condition (5).

By the same token, it is also worth pointing out that condition is implicit in studies aimed at estimating productivity (as these do not try to distinguish the marginal cost at the destination level)—see, e.g., Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009) and De Loecker, Goldberg, Khandelwal and Pavcnik (2016).\(^{14}\)

\(^{13}\)See appendix C for the derivation of (5) and a detailed extensive discussion.

\(^{14}\)Olley and Pakes (1996), Levinsohn and Petrin (2003) and Wooldridge (2009) estimate firm-level productivity and thus can infer the average marginal cost over all products and destinations at the firm level. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) estimates the average marginal cost over destinations at the firm-product level. As
2.1.2 Trade Pattern Sequential Fixed Effects (TPSFE)

In this subsection, we introduce and discuss our estimator. As already mentioned, our estimation strategy consists of differentiating out the unobserved marginal costs by expressing all the observations on product \(i\) sold by firm \(f\) to multiple destinations at time \(t\), in terms of deviations from their average. At each point in time, this average will be conditional on the set of destination markets chosen by the firm. Hence, if we compare the observations obtained in our first step across time, the comparison will generally confound genuine cross-market changes in prices and (holding our identification condition) markups across destinations, with variation due to recalculating the mean conditional on different sets of destinations. This is not necessarily a problem for a markup estimator. If the variation in the set of destination is not driven by the exchange rate, it can be shown that an estimator that works in a balanced panel also works in an unbalanced one (see appendix). However, if the set of destination is systematically related to the exchange rate, the estimates will be biased.

To make sure that empirical results are not contaminated by this problem, we propose an approach based on comparison of observations for identical trade patterns—these are defined as sets of destinations that may repeat identically over time for each firm.\(^{15}\) We then specify a regression model where the trade-patterns so defined are a fixed effect. In other words, we regress product prices in deviations from means on exchange rates, controls and the trade-pattern fixed-effect. By doing so, we effectively ‘demean’ observations one more time—to make sure that, when we compare observations over time, these are always calculated as deviations from a mean from an identical set of destination markets. In other words, the comparison is ‘apples-to-apples’ across sets of firm-product prices in different periods.

We dub this estimator “trade pattern sequential fixed effects” (TPSFE)—designed to address the bias associated with endogenous shift in trade destinations.\(^{16}\) The following describes the exercise, in appendix C.4, we explore an extension of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) in which we add a destination dimension to production costs. We discuss the assumptions that would be required in a structural framework for (5) to be satisfied. Specifically, we allow the functional form of the production function to be firm-product specific with a log-additive productivity term that is firm-product-destination specific. Note that De Loecker, Goldberg, Khandelwal and Pavcnik (2016) would not be identifiable under these assumptions as their identification strategy requires some degree of separability in the functional form in which they have assumed the production function to be product-specific and the Hicks-neutral productivity to be firm-specific. In this extended framework, we show that our identification strategy recovers an unbiased estimate of the markup elasticity even when the marginal cost at the firm-product level varies across destinations, but only if the production function is constant return to scale. It is only when changes in relative demand across destinations lead to relative changes in quantities (which are associated with changes in destination-specific marginal cost) that condition (5) will be violated. This is only the case if the production function is destination-specific. Under the standard assumptions of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) where the production function is not destination-specific, our estimator yields unbiased estimates with constant return to scale (CRS), increasing return to scale (IRS) and decreasing return to scale (DRS) production functions.

\(^{15}\)See the appendix D.4 for a detailed discussion and an example.

\(^{16}\)The importance of bias in unbalanced panels with selection has long been discussed in labor economics, and
implementation of the TPSFE, detailing a three-step procedure.

1. Demean each variable in the dataset at the firm-product-time level, so to express each variable as a destination-specific deviation from the mean. This step strips out firm’s time-varying marginal production cost, as well as any global factor that is common across all the destinations a firm serves.

   (a) For each firm-product-time triplet, calculate the mean of each dependent and independent variable over all destinations the firm serves, i.e., calculate:

   \[
   \frac{1}{n_{D}^{f,i,t}} \sum_{d \in D_{f,i,t}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\}
   \]  

   where \(n_{D}^{f,i,t}\) is the number of foreign destinations for each firm-product-time triplet.

   (b) Remove the mean over all destinations in order to obtain the residual variation in the variable by destination:

   \[
   \tilde{x}_{ifdt,D_{f,i,t}} = x_{ifdt} - \frac{1}{n_{D}^{f,i,t}} \sum_{d \in D_{f,i,t}} x_{ifdt} \quad \forall x \in \{p_{ifdt}, e_{dt}, X_{dt}\}
   \]  

2. Identify the trade pattern for each product sold by a firm in each time period and turn this information into a “trade pattern fixed effect” that incorporates information about the destination associated with each observation as well as the set of all destinations reached by the firm-product in that period.

   For each firm-product-time \((f, i, t)\) triplet:

   (a) Collect the set of destinations served:

   \[
   \{d : p_{if't'dt'} \text{ is observed} : i' = i, f' = f, t' = t\}. \]

   (b) Generate a string variable that identifies this set of destinations. For example, VN-KR-JP is attached to a firm \(f\) which exports product \(i\) to Vietnam, Korea, and Japan in a
year $t$. Notationally, denote this string as $D_{if}$.

(c) Create a trade pattern fixed for each $ifdt$ observation by appending the destination country for that observation to the front of its trade pattern string. For example, for the trade pattern fixed effects VN-VN-KR-JP, KR-VN-KR-JP and JP-VN-KR-JP, the first string is associated with a firm’s shipment to Vietnam in a year in which the firm sells to Vietnam, Korea and Japan. The second string is associated with that firm’s shipment to Korea in the same year, etc. Notationally, denote this trade pattern fixed effect as $TP_{d,D_{if}}$.

3. Run a regression using destination-demeaned variables and the trade pattern fixed effects.

$$\bar{p}_{ifdt,D_{if}} = \kappa_0 + \kappa_1 \bar{e}_{dt,D_{if}} + \bar{X}_{dt,D_{if}}' \kappa_2 + TP_{d,D_{if}} + \bar{u}_{ifdt,D_{if}}$$

(9)

where $e_{dt}$ is the bilateral exchange rate ($rmb/d$) and $X_{dt}$ is a vector of destination-specific macro variables including local CPI and real GDP.

At this point, it may seem impossible to estimate equation (9) because both the dependent variable, price, and the dummy variable, $TP_{d,D_{if}}$, vary along four dimensions. However, variation in $TP_{d,D_{if}}$ is limited and depends on the count of trade patterns, $D_{if}$, in the dataset. In practice, an exporter’s trade pattern, i.e., its chosen set of foreign markets, is not random. As a result, variation in the TPSFE dummy variable, $TP_{d,D_{if}}$, is much smaller than the total number of observations, making equation (9) identifiable.

Overall, the reliability of our empirical framework rests on its capacity to address the two fundamental issues we raised at the beginning of this section, the endogenous selection of markets and the possibility that marginal costs are destination-specific.$^{17}$ In appendix C, we compare our proposed estimator to commonly used alternatives. Subsections C.2 and C.3 in the appendix carry out a series of assessments with the goal of exploring the bias that may arise from an endogenously unbalanced panel and destination-specific marginal costs under a range of reasonable parameters. Subsection C.4 gives a structural interpretation of the identification condition.

2.2 An estimator of firms’ cross-market supply elasticity

We now turn to the flip side of the destination-specific markup adjustment, that is, the adjustment of export quantities across destination markets. We are interested in gaining insight into the

$^{17}$A recent paper by Han (2018) documents that Chinese firms’ entry into and exit from foreign destinations is a function of bilateral exchange rate movements; this confirms the importance of appropriately controlling for endogenous selection of markets.
relationship between destination-specific quantity and markup adjustments within a firm (and product) due to changes in relative demand conditions across destinations.\footnote{The question can be addressed in different ways. One option is to regress quantities directly on exchange rates using the same specification as our TPSFE for destination-specific markups, \eqref{eq:9}. However, the option that we prefer consists of regressing quantities on projections of prices on exchange rates. The two procedures yield very similar results.}

Towards this goal, we construct the following two-stage estimator. In the first stage, we rely on our TPSFE to obtain predicted prices, $\hat{p}_{ifdt,Di_{ft}}$, using specification \eqref{eq:9}:

$$\hat{p}_{ifdt,Di_{ft}} = \kappa_0 + \kappa_1 \tilde{e}_{dt,Di_{ft}} + \tilde{X}'_{dt,Di_{ft}} \kappa_2$$ \hfill \eqref{eq:10}

In the second stage, we use the predicted prices as explanatory variables in the ‘quantity’ equation \eqref{eq:11} specified below

$$\tilde{q}_{ifdt,Di_{ft}} = \gamma_0 + \gamma_1 \hat{p}_{ifdt,Di_{ft}} + \tilde{X}'_{dt,Di_{ft}} \gamma_2 + TP_{d,Di_{ft}} + \tilde{v}_{ifdt,Di_{ft}}$$ \hfill \eqref{eq:11}

Statistically, $\hat{p}_{ifdt,Di_{ft}}$ reflects variation in relative prices driven by changes in the relative market condition measure, $\tilde{e}_{dt,Di_{ft}}$, while controlling for other aggregate variables. The coefficient $\gamma_1$ measures the projection of changes in relative quantities on destination-market-condition-driven changes in relative prices.

As long as cost-side factors are perfectly controlled, $\hat{p}_{ifdt,Di_{ft}}$ can be interpreted as the change in relative markups denominated in the exporter’s currency in response to changes in relative demand conditions across destinations.\footnote{The cost-side factors are controlled if the identification condition \eqref{eq:5} is satisfied.} Heuristically, holding the supply curve fixed, a shift in relative demand induces a movement along the relative supply curve. In this light, $\gamma_1$ could be seen as the slope of the relative supply curve— that is, it captures the cross-market supply elasticity (CMSE) with respect to destination-specific demand changes.

To appreciate the properties of our estimator, we also run a na"ive regression of relative quantity changes on relative prices changes, including trade pattern fixed effects:

$$\tilde{q}_{ifdt,Di_{ft}} = \lambda_0 + \lambda_1 \hat{p}_{ifdt,Di_{ft}} + \tilde{X}'_{dt,Di_{ft}} \lambda_2 + TP_{d,Di_{ft}} + \tilde{v}_{ifdt,Di_{ft}}$$ \hfill \eqref{eq:12}

As shown in section 4, this na"ive regression typically results in a significant but negative correlation: a negative $\lambda_1$ indicates that a higher relative price in one destination is on average associated with a lower relative quantity sold by the firm in that destination. In contrast, our two-stage procedure generates a positive $\gamma_1$, suggesting that the relative markups and quantities are positively correlated if changes in markups are driven by (relative) demand changes. See appendix \ref{app:B.2} for an analytic discussion.
2.3 A new product classification based on Chinese measure words: Refining Rauch (1999) on high and low differentiation products

For the purpose of our analysis, it is important that we identify products over which firms are potentially able to exploit market power in setting prices. For this identification, most studies adopt the industry classifications set forth by Rauch (1999), according to which a product is differentiated if it does not trade on open exchanges and/or its price is not regularly published in industry sales catalogues. While this system is quite powerful in identifying commodities, a drawback is that the vast majority of manufactured goods end up being classified as differentiated.

We construct a new, finer classification. The core idea is a simple one: traded goods whose quantity is recorded in customs data by weight or volume are less differentiated than goods whose quantity is reported in countable units. Chinese customs data provide a unique opportunity to extend this simple idea into an exogenous classification system because the choice to record a product’s quantity in units versus mass is predetermined by Chinese grammar and linguistics. We exploit linguistic information on “measure words” recorded in the Chinese Customs Database to construct a general product classification for the Harmonized System.

As further detailed below, the Chinese Customs Database reports the universe of China’s exports and imports at the firm and Harmonized System 8-digit (HS08) product level annually from 2000 to 2014. The key variables for our analysis are the export value, the export quantity, and a Chinese-language measure word describing the quantity. The information embedded in the measure word is intrinsically informative about the nature of the good and forms the basis for our classification system. To wit: linguists sort Chinese measure words into two groups—mass classifiers and count classifiers.\(^{20}\) Count classifiers are used to measure distinct items while mass classifiers are used to measure things that are naturally measured by weight, volume, length, etc.\(^{21}\) Our classification criterion is as follows: any good whose quantity is reported with a count classifier is a high differentiation good while goods whose quantity is reported with a mass classifier are low differentiation goods. When integrated with the Rauch system, we indeed verify that almost all commodities traded on open exchanges are reported with mass classifiers—fully consistent with our view that mass classifiers identify low differentiation products.


\(^{21}\)More precisely, Cheng and Sybesma (1998) explain: “while massifiers [mass classifiers] create a measure for counting, count-classifiers simply name the unit in which the entity denoted by the noun it precedes naturally presents itself. This acknowledges the cognitive fact that some things in the world present themselves in such discrete units, while others don’t. In languages like English, the cognitive mass-count distinction is grammatically encoded at the level of the noun..., in Chinese the distinction seems to be grammatically encoded at the level of the classifier” (emphasis added).
Table 1: Measure word use in Chinese customs data for exports, 2008

<table>
<thead>
<tr>
<th>Quantity Measure</th>
<th>Meaning</th>
<th>Types of goods</th>
<th>Percent of export value</th>
</tr>
</thead>
<tbody>
<tr>
<td>qián kè, 千克</td>
<td>kilogram</td>
<td>grains, chemicals</td>
<td>40.5</td>
</tr>
<tr>
<td>tài, 台</td>
<td>machines</td>
<td>engines, pumps, fans</td>
<td>24.7</td>
</tr>
<tr>
<td>gè, 个</td>
<td>small items</td>
<td>golf balls, batteries, spark plugs</td>
<td>12.8</td>
</tr>
<tr>
<td>jiàn, 件</td>
<td>articles of clothing</td>
<td>shirts, jackets</td>
<td>6.6</td>
</tr>
<tr>
<td>shuāng, 双</td>
<td>paired sets</td>
<td>shoes, gloves, snow-skis</td>
<td>2.6</td>
</tr>
<tr>
<td>tiáo, 条</td>
<td>tube-like, long items</td>
<td>rubber tyres, trousers</td>
<td>2.5</td>
</tr>
<tr>
<td>mǐ, 米</td>
<td>meters</td>
<td>camera film, fabric</td>
<td>2.1</td>
</tr>
<tr>
<td>tào, 套</td>
<td>sets</td>
<td>suits of clothes, sets of knives</td>
<td>1.8</td>
</tr>
<tr>
<td>liàng, 辆</td>
<td>wheeled vehicles</td>
<td>cars, tractors, bicycles</td>
<td>1.4</td>
</tr>
<tr>
<td>sōu, 隹</td>
<td>boats</td>
<td>tankers, cruise ships, sail-boats</td>
<td>1.3</td>
</tr>
<tr>
<td>kuài, 块</td>
<td>chunky items</td>
<td>multi-layer circuit boards</td>
<td>0.7</td>
</tr>
</tbody>
</table>

For 2008, the dataset reports quantity using 36 different measure words. To illustrate the variety of measures used, table 1 reports a selection of measure words, the types of goods that use the measure word, and the percent of export value that is associated with products described by each measure word. In this table, qián kè (千克) and mǐ, (米) are mass classifiers; the remaining measure words are count classifiers. The main point to be drawn from the table is that the nature of the Chinese language means that the reporting of differentiated goods, for example, automobiles, spark plugs and engines, takes place by reporting a number of items and the associated unique counter that is associated with that type of good. See appendix D.7 for additional examples of the Chinese quantity measures in our data.

Table 2 demonstrates the value added and power of our classification system in relation to that by Rauch. In the table, we integrate our classification of high versus low differentiation goods with that obtained by mapping HS06 product codes to Rauch’s original 4 digit SITC rev. 2 classification of differentiated, reference priced, and open exchange traded goods. The improvement is on at least two dimensions. First, our classification refines the class of differentiated goods in Rauch’s. From table 2 panel (a), we observe that 79.8 percent of observations are classified by Rauch as differentiated. Of these, only 48.6 percent (38.8/79.8) use count classifiers and are categorized as high differentiation under the CCHS approach. The picture is similar in panel (b), where observations are value weighted: of the 71.3 percent of the export value classified by Rauch as differentiated, 66.1 percent (47.1/71.3) uses count classifiers.22 Second, every good that

---

22We have constructed a concordance for all HS06 products as high differentiation or low differentiation by categorizing as high differentiation those HS06 product groups in which all HS08 products use a count classifier. This means that the CCHS classification of differentiated goods can be applied to the customs datasets for other
Table 2: Classification of goods: Integrating the insights from CCHS with Rauch

(a) Share of goods by classification: observation weighted

<table>
<thead>
<tr>
<th>Corsetti-Crowley-Han-Song (CCHS)</th>
<th>Low Differentiation / (Mass nouns)</th>
<th>High Differentiation / (Count nouns)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rauch (Liberal Version)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Differentiated Products</td>
<td>41.1</td>
<td>38.8</td>
</tr>
<tr>
<td>Reference Priced</td>
<td>6.9</td>
<td>0.7</td>
</tr>
<tr>
<td>Organized Exchange</td>
<td>0.6</td>
<td>0.0</td>
</tr>
<tr>
<td>Unclassified†</td>
<td>10.5</td>
<td>1.5</td>
</tr>
<tr>
<td></td>
<td><strong>59.1</strong></td>
<td><strong>40.9</strong></td>
</tr>
<tr>
<td></td>
<td><strong>100.0</strong></td>
<td></td>
</tr>
</tbody>
</table>

(b) Share of goods by classification: value weighted

<table>
<thead>
<tr>
<th>Corsetti-Crowley-Han-Song (CCHS)</th>
<th>Low Differentiation / (Mass nouns)</th>
<th>High Differentiation / (Count nouns)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Rauch (Liberal Version)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Differentiated Products</td>
<td>24.2</td>
<td>47.1</td>
</tr>
<tr>
<td>Reference Priced</td>
<td>9.1</td>
<td>2.8</td>
</tr>
<tr>
<td>Organized Exchange</td>
<td>2.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Unclassified†</td>
<td>11.9</td>
<td>2.9</td>
</tr>
<tr>
<td></td>
<td><strong>47.2</strong></td>
<td><strong>52.8</strong></td>
</tr>
<tr>
<td></td>
<td><strong>100.0</strong></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. †: The “Unclassified” category refers to HS08 products that do not uniquely map to the SITC Rev. 2 classification of Rauch.
Rauch categorizes as a commodity (an open-exchange traded good) is reported in the Chinese Customs Database with a mass classifier. This conforms with our prior that mass nouns are low differentiation goods.

A final, further benefit of our classification system is that we are able to provide a classification for goods that a concordance between HS06 and SITC Rev. 2 leaves unclassified under Rauch’s system. Note that around 12% percent of observations in panel (a) (and 14.8% of observations in panel (b)) do not uniquely map to a single Rauch category. They do according to our classification.\(^{23}\)

3 Data

To construct the dataset in this paper, we merge information from two datasets: (1) the Chinese Customs Database, i.e., the universe of annual import and export records for China from 2000 to 2014 and (2) annual macroeconomic data from the World Bank. Moreover, we turn to administrative data from Her Majesty’s Customs and Revenue (HMCR) in the UK to provide information about the currency of invoicing of Chinese exports so that we can place our results in context.

We begin with the Chinese Customs Database that reports detailed trade flows (quantities and values) at the firm-product-destination level. In addition to standard variables, such as the firm ID, an 8-digit HS code, the destination country and year\(^ {24}\), the database contains the Chinese measure word in which quantity is reported, an indicator of the form of commerce for tax and tariff purposes, and a categorization based on the registration type of the exporting firm.\(^ {25}\)

Like other firm-level studies using customs databases, we use unit values as a proxy for prices. However, the rich information on forms of commerce, and Chinese measure words enables us to build more refined product-variety categories than prior studies have used. Specifically, we define the product identifier as an 8-digit HS code + a form of commerce dummy + a CCHS classification categories.

\(^{23}\)The problem that arises is that the concordance of disaggregated HS06 product codes to (more aggregated) SITC Rev.2 involves 1-to-many or many-to-many mappings for 81 percent of concordance lines. Therefore, we cannot identify a unique mapping from HS06 to a Rauch-based SITC rev. 2 classification for 12% of observations in the Chinese Customs Database.

\(^{24}\)The database is available at the monthly frequency during the period 2000-2006 and annual frequency during the period 2007-2014. We aggregate the monthly data for 2000-2006 to the annual level in this study.

\(^{25}\)The form of commerce indicator records the commercial purpose of each trade transaction including “general trade,” “processing imported materials,” and “assembling supplied materials,” etc. The registration type variable contains information on the capital formation of the firm by 8 categories: namely state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign owned enterprise, collective enterprise, private enterprise, individual business, and other enterprise. In our later analysis, we group three types of foreign-invested firms, namely wholly-foreign-owned enterprise, Sino-foreign contractual joint venture and Sino-foreign equity joint venture, into one category and dub it as “foreign invested enterprises.” We group minority categories such collective enterprise, individual business and other enterprise into one category and refer to them as “other enterprises.”
The application of our product-variety definition generates 14,611 product-variety codes as opposed to the roughly 8,100 8-digit HS codes reported in the database. This refined product measure allows us to get a better proxy of prices for two reasons. First, the inclusion of the information on form of commerce helps to distinguish the subtle differences of goods being sold under the same 8-digit HS code. Second, the extensive use of a large number of measure words as quantity reporting units makes unit values in Chinese data conceptually closer to transactions prices than unit values constructed with other national customs datasets.

The Chinese Customs Database reports transactions denominated in US dollars. We calculate the price in the exporter's currency (renminbi) by multiplying the unit value of dollar transactions with the annual renminbi-dollar rate.

4 Empirical Results

In this and the next section, we present and discuss results obtained by applying our empirical framework to the Chinese Customs Database. In this section, we will first present our estimates on markup adjustment, and cross-market supply elasticities for the whole sample of Chinese exports. Then we will present estimates distinguishing between high and low differentiation goods. In the next section, we will refine our analysis by by grouping firms according to their registration type, distinguishing private and public, as well as domestic and foreign ownership.

To make our results comparable with leading studies in the literature on exchange rate pass through, we apply the TPSFE estimator following the same methodology as Gopinath, Itskhoki and Rigobon (2010) and condition our estimates on a price change. Specifically, we estimate all parameters after applying a data filter to the Chinese export data: for each product-firm-destination combination, we filter out absolute price changes in renminbi smaller than 5 percent. Thus, our pass-through estimates are based on S-period differences in prices, relative to the change in the exchange rate and other macro variables cumulated over the same S-period. The S-period interval defining a price change can vary within a firm-product-destination triplet and across these

\footnote{Firms in the Chinese Customs Database can produce the same product under two or more forms of commerce. Essentially, a good could be produced under different tax regulations depending on the exact production process used. In creating our form of commerce dummy, we generate a dummy variable equal to 1 if the transaction is “general trade” and 0 otherwise. The CCHS classification dummy equals 1 if the product is a high differentiation product and 0 if the product is a low differentiation product.}

\footnote{The primary reason why the number of product-varieties exceeds that of HS08 products is due to the addition of the form of commerce dummy.}

\footnote{Important previous studies have constructed unit values (export value/export quantity) from data in which quantity is measured by weight (Berman, Martin and Mayer (2012)) or in a combination of weights and units (Amiti, Itskhoki and Konings (2014)).}

\footnote{Note that because our TPSFE estimator differences out the common components across destinations, using prices denominated in dollars with dollar-destination exchange rates versus using prices denominated in renminbi with renminbi-destination exchange rates in the estimation procedure yields exactly the same estimates.}
triplets. That is, for a single firm-product-destination triplet, we might observe S-period differences of, say, 2, 3, 4 or more years, within the 15 years included in our panel. We provide an example on how the price change filter is constructed and how trade patterns are subsequently formulated based on the price-change-filtered database in appendix D.4.

One advantage of carrying out our estimations conditional on a price change is that we can clarify the differences between our estimators and exchange rate pass-through estimators. As a reference benchmark, all our tables include estimates of the export price elasticity to the exchange rate (the complement of exchange rate pass through) obtained by following standard methodologies. This will allow us to quantify the relative contribution of the destination-specific markup elasticity (obtained by using our TPSFE estimator) to total export price adjustment.

![Renminbi Movements 2000-2014](image)

**Figure 1: Renminbi Movements 2000-2014**

We report results separately for the subsamples corresponding to the two exchange rate regimes pursued by China, the fixed exchange rate regime of 2000-2005 and the managed float regime of the latter period. Figure 1 plots the bilateral movement of the renminbi against the US dollar, as well as China’s nominal effective exchange rate, over our entire sample period. As will be discussed in later sections, there is evidence that exporters’ pricing behavior differs across the two environments.

Throughout our analysis, we treat eurozone countries as a single economic entity and integrate their trade flows in a single economic region.\(^{30}\) In addition, we exclude exports to the US and

---

\(^{30}\)Specifically, we aggregate the export quantity and value at the firm-product-year level for 17 eurozone countries including Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovakia, Slovenia and Spain. Latvia and Lithuania joined the eurozone in 2014 and 2015,
Hong Kong to ensure comparability of our estimates across regimes.

4.1 Markup adjustments and incomplete pass through

Applying our estimator to our entire sample of exports (without distinguishing goods by their degree of differentiation), we find that, on average, destination-specific markup adjustments are moderate, and account for a non-negligible share of incomplete pass through into import prices. Their quantitative importance, however, increased after China abandoned its strict peg to the dollar in 2005. Since the degree of exchange rate pass through is relatively high, markup adjustments account for a non-negligible share of the incomplete pass through into import prices.

Estimation results are shown in Table 3. We start by considering standard ERPT estimates, shown in columns (1) and (2) in the table. In reading the results on these columns, it is important to keep in mind that we measure export prices in renminbi and bilateral exchange rates as renminbi per unit of foreign currency—a low coefficient on the export price elasticity in columns (1) and (2) means a high pass through into import prices in foreign (local) currency.

As shown in the table, the elasticity of export prices (in renminbi) to bilateral exchange rates is low and stable across the two subsamples. On average, conditional on a price change, the renminbi price of Chinese exports responds to nominal bilateral exchange rate movements by 23% over the 2000-2005 period and 24% over 2006-2014 period. These estimates mean that pass through into import prices in local currency in destination markets is, on average, high and stable over time: it was about 77% in the years of China’s currency peg and essentially the same, 76%, in later years. Note that the coefficients on the destination real GDP and the import share of GDP, meant to capture the export price response to factors specific to the destination market, have positive signs, as expected. Also, observe that the destination CPI has a sizeable, positive effect on export prices and that this increases substantially after the renminbi is unpegged from the US dollar.

To understand the difference between ERPT and our estimator, it is useful to decompose the price adjustment into three components: (a) a general markup adjustment that is the same across all markets, (b) a destination-specific markup adjustment, and (c) any marginal cost change. When we estimate the price elasticity to the exchange rate (columns 1 and 2), our estimate of the price respectively. We treat them as separate countries throughout our analysis.

Our results are robust to the inclusion and exclusion of small countries that adopted the euro in the later period of our sample. We performed two robustness checks. One excludes Slovenia, Cyprus, Malta, Slovakia and Estonia from the eurozone group and treats them as separate individual countries, resulting in an estimation sample of 159 destinations. Another excludes Slovenia, Cyprus, Malta, Slovakia and Estonia from the eurozone group and drops these five countries from our estimation sample, resulting in an estimation sample of 154 destinations. These two alternative estimation samples yield very similar results to our primary estimation sample (154 destinations) which integrates 17 eurozone countries together.

For macroeconomic series, we use the World Bank reported CPI index, bilateral exchange rates and import-to-GDP ratio for the euro area. We construct a “GDP constant local currency” measure for the eurozone using the reported “GDP constant US dollar (2010)” variable and the 2010 euro-dollar rate.
Table 3: Price and Markup Elasticities to Exchange Rates

<table>
<thead>
<tr>
<th></th>
<th>Price Elasticity (1-ERPT)</th>
<th>Markup Elasticity (Destination-specific)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Bilateral nominal exchange rates</td>
<td>0.23***</td>
<td>0.24***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Destination CPI</td>
<td>0.09***</td>
<td>0.58***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Destination real GDP</td>
<td>0.41***</td>
<td>0.05***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Import-to-GDP ratio</td>
<td>0.22***</td>
<td>0.30***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Observations</td>
<td>516,552</td>
<td>3,050,928</td>
</tr>
<tr>
<td>FE</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>SE</td>
<td>Robust</td>
<td>Robust</td>
</tr>
<tr>
<td>Con Price Change</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. The “Markup Elasticity” columns present estimates from our TPSFE estimator. Both the “Price Elasticity” and the “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix D.4. Note that constructing S-period time differenced variables will result in a smaller number of observations compared to fixed effect approaches as the initial year of each firm-product-destination triplet becomes a missing value when we take time differences. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.
adjustment is a mixture of movements in all three components mentioned above: the coefficient captures the average of the price elasticity to bilateral exchange rates across all markets. In comparison, our TPSFE estimator captures the average of the relative price adjustments to the relative exchange rate movements across all markets—hence it accounts for (b). Under our identification condition, the relative price adjustment is equivalent to the relative markup adjustment across destinations, i.e., the destination-specific adjustment of the markup.

In columns (3) and (4), we report our estimated destination-specific markup elasticities. Conditional on a price change in renminbi occurring at \( t + s \), the average destination-specific markup changes by 7% of the cumulated bilateral exchange rate movement between \( t \) and \( t + s \) during the dollar peg period (column 3). After the change in the exchange rate regime, as shown in column (4), the destination-specific markup response rises to 11% of the cumulated movement. These results suggest that, on average, firms became considerably more active in adjusting their destination-specific markups after China abandoned its strict peg to the US dollar.\(^{31}\)

The differences in markup elasticities we detect across our subsamples are likely to reflect more than just the policy switch from a dollar peg to a managed float in China. They may stem from structural changes at the firm and market level, as well as from changes in the frequency and importance of cyclical (policy and technology) shocks at the national and global level that have occurred between the two time periods.\(^{32}\) We build a general multi-country framework for a more rigorous discussion and interpretation of our empirical estimates in Appendix A.

### 4.2 High versus low differentiation goods

We now turn to our results from disaggregating the sample according to our product classification. To introduce and motivate disaggregated our analysis, we find it instructive to discuss two products as case studies, and visualize graphically the relationship between changes in relative markups and movements of relative exchange rates, using our destination-demeaned variables. We select canned tomato paste (measured in kilograms), as representative of low differentiation manufactured goods according to our CCHS classification, and wheeled tractors (measured with “liang”), as a high differentiation good.

---

\(^{31}\)In columns (3) and (4) we also estimate a tiny markup adjustment to the idiosyncratic component of local CPI growth over 2000-2005 (column 3) and no change in the later period (column 4). The difference in estimated coefficients on CPI in columns (1) versus (3) and (2) versus (4) arises because our approach removes the global trend in the exporter’s price associated with global CPI movements and isolates the local component.

\(^{32}\)The price elasticity provides different information relative to estimates of pass through that are made conditional on a specific shock hitting the economy – a point elaborated at length by Corsetti, Dedola and Leduc (2008). To wit: we would expect the price response to exchange rate movements to be quite different if the underlying shock is to productivity as opposed to monetary policy. Estimates of pass through conditional on a shock require methodologies, like VARs, suitable to identifying these shocks in isolation and tracing their effects on the exchange rate, export prices, and markups – see Forbes, Hjortsoe and Nenova (2017).
In figure 2, we plot the dispersion of markups across destinations for the top three exporters of tomato paste (upper panel) and wheeled tractors (lower panel) in 2007 and 2008. For each annual observation of a sale, we calculate the deviation of the sales price from its mean across destinations within the firm-product-year triplet (where sales price is the log unit value in renminbi), i.e. \( w_{ifd} - \bar{w}_{if} \), and plot these deviations using different shapes (i.e., triangle, square, and circle) for each firm. The x-axis measures positive and negative deviations of the sales price from the mean value in 2007; the y-axis measures the deviations from the mean in 2008. Any observation on the 45 degree line is a product whose relative markup in its destination did not change between 2007 and 2008. Thus, a point lying on the 45 degree line at, say, 0.2 represents a product that was sold in some destination at a 20% premium over the firm’s mean price in both 2007 and 2008. An observation plotted above the 45 degree line depicts a product-destination whose markup increased between 2007 and 2008 relative to the firm’s sales of the good in other destinations. Conversely, an observation plotted below the 45 degree line represents a product-destination that saw its relative markup fall.

We color code each point representing a firm-product-destination triplet according to whether the destination’s currency appreciated or depreciated during 2007-2008 relative to the other destinations the firm was selling to. Red indicates relative appreciation, blue relative depreciation. Above and below the 45 degree line, we report the number of observations marked by red dots, corresponding to bilateral appreciations, in ratio to the number of observations marked by blue dots corresponding to depreciations.

Three important features are captured in these graphs. First, the relative markups for many firm-product-destination triplets, measured in the producer’s currency, change from year to year. Second, the low differentiation good, tomato paste, exhibits less dispersion in its markups across destinations than the high differentiation good, wheeled tractors. Third and most importantly, for high differentiation goods, appreciation of the destination market currency relative to the renminbi is associated with an increase in relative markups—red dots are denser above the 45 degree line—, while depreciation of the destination market currency is associated with a decrease in relative markups. No such clear pattern emerges between relative markup changes and relative currency changes for the low differentiation good, tomato paste.

These two cases illustrate well the characteristic features of firm-level pricing that drive our econometric estimates presented below.

---

The magnitude of price dispersion within a year across destinations for wheeled tractors is of the same order of magnitude as that found in European automobile prices in an important study of international market segmentation by Goldberg and Verboven (2001).
Example 1: Canned Tomato Paste (a low differentiation product)

Example 2: Wheeled Tractors (a high differentiation product)

Note: Firm-level markup dispersion for tomato paste (HS20029010) and wheeled tractors (HS87019011) is calculated as the deviation from the mean log unit value, denominated in RMB, across destinations at the firm-product-year level, i.e., $u_{zft} - \overline{w}_{zft}$. For this figure, we begin with a balanced panel of firm-product-destination observations for two consecutive years, 2007 and 2008, and plot the observations of markup dispersion for the top three firms based on the number of observations in the constructed balanced panel. Red observations are for destinations whose currency appreciated relative to the renminbi between 2007 and 2008 while blue observations are for destinations whose currencies depreciated.
4.2.1 Markup elasticities using the CCHS product classification

In line with our discussion of the two case studies above, our econometric analysis documents significant differences in both pass through and markup elasticities across high and low differentiation goods. Overall, product differentiation appears to be a good proxy for market power, validating the usefulness of our linguistics-inspired product classification.

Results are shown in table 4. For comparison, the first two columns of the table reproduce the key results from table 3, average export price and markup elasticities for the universe of Chinese exports. The remaining four columns report results for the subsamples of high and low differentiation goods. The first row refers to the dollar peg period, the second row to the more recent period in the sample. In both subperiods, the renminbi prices and markups of high differentiation goods respond more to bilateral exchange rates movements, implying lower ERPT, than low differentiation goods. For the latter group of goods, pricing-to-market actually plays no role during the dollar peg, and only a moderate role after the strict peg is abandoned.

Focusing on quantitative results: during the fixed exchange rate period (row 1), we have already seen that the markup elasticity over all goods is relatively small, 7% (column (2)). The results in the table show that this low average estimate conceals important differences across types of good. For CCHS high differentiation exports, the markup elasticity is as high as 14%—for low differentiation goods it is as low as 2% and statistically indistinguishable from zero.

In the period of the managed float of the renminbi (second row of table 6), markup elasticities are considerably higher. For high differentiation goods, the export price elasticity rises from 25 to 32% (and exchange rate pass through correspondingly falls to 1-.32=.68); the markup elasticity rises from 14 to 20%. Note that the markup adjustment to the exchange rate accounts for two-thirds of the price elasticity (0.20/0.32). For low differentiation goods, the markup elasticity is smaller but becomes significantly positive, at 6%. This accounts for one-third of the adjustment in renminbi prices, estimated at 19%.

4.2.2 Integrating the CCHS product descriptions with UN end-use categories

Firms selling directly to consumers typically engage in branding and advertising campaigns to a much larger extent than firms selling intermediate products. Insofar as consumption goods producers are successful in making their products less substitutable with other products or product varieties, markets for consumption goods should be less competitive than markets for intermediates. Thus, we may expect markup elasticities to be higher for consumption goods than for intermediates.

To gain further insight on how the intensity of market competition can impact pricing by firms, we now split our data combining our CCHS classification with the classification of consumption
Table 4: Price and Markup Elasticities by CCHS Classification

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>High Differentiation</th>
<th>Low Differentiation</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price</td>
<td>Markup</td>
<td>Price</td>
<td>Markup</td>
</tr>
<tr>
<td>2000 – 2005</td>
<td>0.23***</td>
<td>0.07***</td>
<td>0.25***</td>
<td>0.14***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>2006 – 2014</td>
<td>0.24***</td>
<td>0.11***</td>
<td>0.32***</td>
<td>0.20***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. “Markup Elasticity” columns present estimates from our TPSFE estimator. Both “Price Elasticity” and “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix D.4. Destination CPI, real GDP and M/GDP controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbi per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

goods and intermediates under the UN’s Broad Economic Categories (BEC).\(^{34}\) Results are shown in Table 5.

In line with our argument above, the price-setting behaviour is quite different across the two types of goods. The estimated markup elasticities are higher for consumption goods than for intermediates, both in the dollar peg years and the managed float period. During the dollar peg era, the markup elasticity is sizeable for consumption goods (0.10, row 1, column (2)), but not statistically significant for intermediate goods (row 2, column (2)). Observe that consistent with our results in table 3, after China abandoned the dollar peg, the magnitudes of markup elasticities increase for both consumption goods (0.20, row 3, column (2)) and intermediates (0.05, row 4, column (2)).

Within each end-use category, we can still detect higher markup elasticities for high differentiation relative to low differentiation goods. During the dollar peg period (top panel of the table), markup elasticities are significantly different from zero only for high differentiation goods—consumption goods exhibit the largest value (0.17, row 1, column (4)), followed by intermediates (0.14). Under the managed float, markup elasticities are positive and significant for all types of goods, pointing to extensive pricing-to-market. Our estimated elasticity actually peaks for high differentiation consumption goods (0.32, row 4 column (4)), almost three times the value for high differentiation intermediates (0.12, row 3 column (6)). The markup elasticities are lower for low differentiation goods, and quite close for consumption and intermediate goods (0.08 and 0.05, rows

\(^{34}\) The UN’s BEC classifies all internationally traded goods according to their end-use. The most disaggregated classification available in BEC Rev. 4 maps HS06 products into end-use categories of consumption goods, intermediate inputs, and capital equipment. For our analysis, all HS08 products into the Chinese Customs Database are assigned the end-use of their corresponding HS06 code.
During the dollar peg, a slightly larger markup elasticity for low differentiation consumption goods (8%) relative to low differentiation intermediates (5%) lends support to the idea that, even within this group of manufactured goods, at least some firms producing consumption goods are successful in acquiring market power. Furthermore, all groups of products experience a rise in markup elasticities with the adoption of the managed float, except for high differentiation intermediate goods, whose markup elasticities are not statistically different during the peg and the managed float period.

As already pointed out, our results are informative on the extent to which incomplete exchange rate pass through can be attributed to a destination-specific markup adjustment, as opposed to common markup adjustment across markets and changes in production costs. During the managed float period, the estimated ERPT into import prices in local currency for high differentiation consumption goods is only 56% (corresponding to an export-price elasticity of 0.44). This is far lower than most estimates using micro firm-level data. In our findings, three-quarters of this incomplete ERPT can be attributed to destination-specific markup adjustments (0.32/0.44, row 3, column (4)/column (3)).

For high differentiation intermediates, pass through into import prices is higher, 66% (1-0.34, row 4, column (3)); however, the fraction of the incomplete pass through due to destination-specific markup adjustments is far smaller—about one-third (0.12/0.34, row 4, column (4)/column (3)). The same is true for intermediate inputs that are low differentiation. For these goods, ERPT is 81% (1-0.19, row 4, column (5)), and the destination-specific markup adjustment explains only about one-quarter of the incomplete pass through.\footnote{The trade policy implications of market power in intermediates characterised by high differentiation or “customisability” are significant; see, e.g., the model by Antràs and Staiger (2012).}
Table 5: Price and Markup Elasticities by BEC Classification

<table>
<thead>
<tr>
<th>Category</th>
<th>Price</th>
<th>Markup</th>
<th>Price</th>
<th>Markup</th>
<th>Price</th>
<th>Markup</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption</td>
<td>0.25***</td>
<td>0.10***</td>
<td>0.29***</td>
<td>0.17***</td>
<td>0.19***</td>
<td>0.02</td>
<td>426,462</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.03)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Intermediate</td>
<td>0.23***</td>
<td>0.03</td>
<td>0.22***</td>
<td>0.14***</td>
<td>0.24***</td>
<td>0.01</td>
<td>294,929</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.06)</td>
<td>(0.05)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. “Markup Elasticity” columns present estimates from our TPSFE estimator. Both “Price Elasticity” and “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix D.4. Destination CPI, real GDP and M/GDP controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

4.2.3 The CCHS and Rauch classification systems compared

According to the Rauch classification system, products traded on open exchanges (OE) are generally regarded as commodities whose prices are expected to fluctuate with global supply and demand. Reference price (RP) products are list-price goods: firms producing them compete somewhat directly by supplying at the price published in some industry-trade publication. These goods are thought to offer a very limited scope for market power in pricing. Conversely, differentiated goods are defined as goods for which prices are not publicly negotiated—which indicate limited direct competition among firms and greater scope for charging markups. As argued above, our linguistics based classification allows us to refine the Rauch classification by distinguishing differentiated goods using two finer categories, and by classifying goods for which there is not enough information about pricing.

To highlight the contribution of our product-feature-based classification system relative to
Rauch (1999)’s market-structure based classification, we now integrate the two in our empirical analysis. Results are shown in table 6.

Table 6: Price and Markup Elasticities by Rauch Classification

<table>
<thead>
<tr>
<th>Category</th>
<th>Price</th>
<th>Markup</th>
<th>Price</th>
<th>Markup</th>
<th>Price</th>
<th>Markup</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Differentiated Products</td>
<td>0.22***</td>
<td>0.09***</td>
<td>0.25***</td>
<td>0.14***</td>
<td>0.20***</td>
<td>0.04**</td>
<td>815,223</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>Organized Exchange</td>
<td>0.60***</td>
<td>0.02</td>
<td>-</td>
<td>-</td>
<td>0.62***</td>
<td>0.02</td>
<td>11,925</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.05)</td>
<td></td>
<td></td>
<td>(0.06)</td>
<td>(0.05)</td>
<td></td>
</tr>
<tr>
<td>Reference Priced</td>
<td>0.23***</td>
<td>0.09**</td>
<td>0.05</td>
<td>0.26**</td>
<td>0.24***</td>
<td>0.08*</td>
<td>88,959</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.04)</td>
<td>(0.16)</td>
<td>(0.12)</td>
<td>(0.04)</td>
<td>(0.04)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Price Elasticity” columns report estimates regressing S-period accumulated changes in renminbi unit values on S-period accumulated changes in nominal bilateral exchange rates and other macro-level control variables. “Markup Elasticity” columns present estimates from our TPSFE estimator. Both “Price Elasticity” and “Markup Elasticity” columns are estimated based on the same estimation sample of filtered price changes following the procedure specified in appendix D.4. Destination CPI, real GDP and M/GDP controls are included in each regression; related estimates are omitted for conciseness. The bilateral exchange rate is defined as renminbis per unit of destination currency; an increase means an appreciation of the destination currency. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Not surprisingly, our estimates of markup elasticities are zero for goods traded in organized exchanges, which in our classification are treated as low differentiation goods (rows 2 and 5, column (2)). However, our estimator detects a positive elasticity for goods that are ‘reference priced’ in Rauch (rows 3 and 6, column (2)), and unveils an increase in market power across the two currency regimes.

The most important takeaway from table 6 is, however, that the estimated markup elasticity of “differentiated” goods according to the Rauch classification, 12% in the later sample, is an average
of very different elasticities for high and low differentiation goods, 20% and 7% respectively.

4.3 Cross Market Supply Elasticity

We conclude this section by investigating the flip side of the markup elasticity to exchange rates, that is, firms’ cross market supply elasticity. The question we ask is to what extent, in response to exchange rate movements, do firms reallocate their output across markets as they adjust their own markups in different destinations. Table 7 presents the estimates obtained by applying the method developed at the end of section 2, together with the results from a naïve regression of relative quantities on relative prices, conditional on the trade pattern fixed effects.

Starting from the naïve regression, 1% increase in relative prices is associated with a 0.7% decline in relative quantities (rows 1 and 2, column (1)). The naïve regression simply reveals that, in equilibrium, firms sell relatively small quantities in markets where they set relatively high prices.36

The result from the naïve regression contrasts sharply with the results from our CMSE estimator. For the managed float regime, over the 2006-2014 period (table 7, row 2), our estimated cross market supply elasticity is positive and equal to 1.51 (row 2, column (2)): a one percent increase in the relative markup (driven by the exchange rate) is associated with 1.5 percent change in the relative quantity across destinations. In relative terms, exports rise in destinations where firms also increase markups in response to a local currency appreciation. What is especially significant here is the change in the sign of the regression coefficient when we apply our method. The CMSE is designed to isolate the relative quantity adjustments across destinations caused by markup adjustments to exchange rate movements.

A positive slope coefficient from the CMSE estimator confirms that our TPSFE approach is able to isolate the demand-side effects of exchange rate fluctuations. The main idea underlying the development of our statistical procedure consists of exploiting relative movements in bilateral exchange rates to trace shifts in the relative demand across a firm’s markets—by projecting relative prices/markups on exchange rates. These projections are then used to trace out a firm’s relative “willingness to supply” across markets.

The most important finding in this table consists of the sharp difference in estimated CMSEs across high and low differentiation goods. Over the 2006-2014 period, the estimated CMSE is very low for high differentiation goods, 0.83 (row 2, column 4), consistent with a view that firms exporting high differentiation products respond to destination-specific exchange rate movements by adjusting markups, rather than by letting the foreign-currency price move substantially with the exchange rate (which would effect a larger adjustment in quantities). In contrast, the estimated

36 This could reflect low levels of competition/high market power, in turn pointing to higher barriers to entry, or fixed costs as an important component of trade costs.
CMSE for low differentiation goods is quite high: a one percent increase in the relative markup is associated with 2.47% increase in the relative quantity supplied. Altogether, these results underscore important heterogeneity in price-setting and quantity responses between high and low differentiation goods.

We know already that exporters from China engaged in only modest amounts of pricing-to-market during the years of the fixed exchange rate regime in our sample. Indeed, over these years, bilateral exchange rate movements are a quantitatively important predictor of destination-specific markup adjustments only for high differentiation goods—with a sizeable 0.14 markup elasticity (see table 4). For these goods, our estimated CMSE is quite high, 2.57. All together, these results suggest that, during the strict peg period, firms responded to bilateral exchange rate movements with modest markup adjustments— they rather aggressively pursued openings for higher profits through large increases in relative quantities, i.e., a 2.57% increase in the relative quantity supplied associated with a 1 percent increase in the relative markup.

**Table 7: Cross Market Supply Elasticity by CCHS Classification**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>High Differentiation</th>
<th>Low Differentiation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Naive Reg.</td>
<td>CMSE</td>
<td>Naive Reg.</td>
</tr>
<tr>
<td>2000 – 2005</td>
<td>-0.71***</td>
<td>4.09***</td>
<td>-0.74***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.82)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>2006 – 2014</td>
<td>-0.70***</td>
<td>1.51***</td>
<td>-0.73***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.16)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>n. of obs</td>
<td>1,076,815</td>
<td></td>
<td>4,863,196</td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naive Reg” column is estimated using specification (12). The “CMSE” column is estimated based on equations (10) and (11). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

**Table 8: Cross Market Supply Elasticity by BEC Classification (2006 – 2014)**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>High Differentiation</th>
<th>Low Differentiation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Naive Reg.</td>
<td>CMSE</td>
<td>Naive Reg.</td>
</tr>
<tr>
<td>Consumption</td>
<td>-0.71***</td>
<td>0.54***</td>
<td>-0.77***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.11)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Intermediate</td>
<td>-0.71***</td>
<td>2.92***</td>
<td>-0.74***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.73)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>n. of obs</td>
<td>1,756,214</td>
<td></td>
<td>1,593,591</td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naive Reg” column is estimated using specification (12). The “CMSE” column is estimated based on equations (10) and (11). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.
We conclude with additional evidence on the extent and importance of international market segmentation and market power. Table 8 reports our CMSE estimates for high and low differentiation goods by Broad Economic Categories. At one extreme we have highly differentiated consumption goods: a very low quantity substitution across destinations suggests that the markets for these goods are highly segmented. At the other extreme, quantity substitution is quite high and markets appear quite integrated for low differentiation exports, especially of intermediates.

5  A Diagnostic for Open Macro Models

Our results on the destination-specific markup elasticity (DSME) and the cross-market supply elasticity (CMSE) provide a valuable diagnostic tool for the development of open economy macro models. In ongoing work, we use them to guide and discipline the specification of a multi-country model encompassing features of leading contributions to the literature.

This section briefly summarizes our results so far—see the appendix A for a detailed discussion. Our theoretical contribution consists of a multi-country model that features different market structures and mechanisms incentivizing firms to optimally engage in pricing-to-market (drawing on, e.g., Atkeson and Burstein (2008) and Corsetti and Dedola (2005)). The goal is to investigate which features are essential for the model to match the markup and quantity elasticities we find in the data.

Our first diagnostic is informed by the patterns documented in section 4, showing how the magnitude of the DSME (CMSE) changes with the extent of product differentiation. In particular, the model should account for the finding that the DSME (CMSE) is increasing (decreasing) as products become more differentiated, or equivalently, as the elasticity of substitution across varieties falls.

The second set of targets for our diagnostic is given by the magnitudes of the estimated elasticities, which differ across types of products (e.g., highly differentiated consumption goods, low differentiation intermediates, etc.). We assess our calibrated open economy macro model by examining its ability to match our evidence, for a standard and reasonable calibration of the fundamental parameters (e.g., ρ, the elasticity of substitution within an industry, η, the elasticity of substitution across industries, etc.).

Our multi-country model has three building blocks. The first building block comes from Atkeson and Burstein (2008) (henceforth AB). These authors model competition among producers using a nested CES structure allowing for variable markups that are increasing in a firm’s local market share. The second building block comes from Corsetti and Dedola (2005) (henceforth CD), which focuses on vertical interactions between international producers and local providers of non-traded distribution services. The CD structure, with its emphasis on the local distribution system,
introduces a local cost component (in nontradable services) into final consumer prices. These local costs in turn affect optimal pricing by upstream producers—reducing the trade elasticity and making optimal markups state-contingent. Combining the features of these two models together integrates what we call, heuristically, ‘horizontal’ and ‘vertical’ dimensions of the market structure relevant for markup adjustment.

Multilateral competition between foreign exporters from different origins is the third, and final block of the model, which we specify with $H > 2$ countries. In light of our main results, the integration of the AB and CD models yields much more than the sum of the parts. A detailed presentation of our full model (dubbed as $ABCD^H$) together with analytical discussions of the mechanisms by which it can match the empirical results is provided in the appendix.

The key theoretical result is that the $ABCD^H$ model can successfully match our two diagnostics, but only if all its three building blocks are integrated in the specification. If we shut down the CD feature of vertical interactions, the AB model in isolation predict that the DSME is decreasing in the level of product differentiation, the opposite pattern relative to our empirical findings. Further, the CMSE is much too high. Conversely, if we shut down the AB features, the CD model with vertical interactions only can account for the qualitative pattern in the data—the DMSE is decreasing in the elasticity of substitution. However, the magnitude of the model-generated elasticities are still far from the empirical targets—the cross-market quantity elasticity is too high. To much the evidence, we need to include also multilateral competition effects from the multi-country specification.

6 Conclusions

The increasing availability of large, multi-dimensional, administrative datasets of firms is enabling researchers to explore new questions into the operation of the global economy, as well as to re-examine classic questions in new ways. In this paper, we have proposed a new empirical strategy that exploits administrative data on exporters in order to examine both markup and quantity adjustments by firms to currency movements. While our motivation for this paper is an analysis of exports, the methodology we developed can be applied to other contexts in which producers sell to multiple markets/buyers and may price discriminate across them.

Our first contribution in this paper is a framework to estimate the export price markup elasticity and the cross-market supply elasticity to the exchange rate. We showed that the TPSFE estimator is capable of controlling for a firm’s time-vary marginal cost at the product level, even when the panel of data is endogenously unbalanced. More importantly, we derive an identification

\footnote{Thus, final consumer prices embody foreign production costs, a markup charged by the foreign producer, and a local distribution margin.}
condition showing that our estimator can remain unbiased even in the presence of destination-specific production costs—so long as the these are not systematically correlated with the exchange rate in growth rates.

Markup adjustments can be expected to vary with the degree of competition in a market. To explore this issue, we have constructed a new, general classification of Harmonized System products aided by a specific feature of Chinese linguistics and information on traded quantities reported to Chinese Customs Authorities. We use a linguistic classification of Chinese measure words, or quantity measures, to classify HS products into high and low differentiation categories and use this to proxy for market power. In conjunction with our TPSFE estimator, this classification allows us to document striking differences in empirical elasticities between high and low differentiation goods. Moreover, it adds value to existing classification systems such as Rauch (1999) and the UN’s Broad Economic Categories.

Our empirical results document significant heterogeneity across categories of goods. We find that firms exporting high differentiation goods from China make moderate but significant destination-specific adjustments to markups in response to movements of bilateral exchange rates—markup adjustments account for up to three quarters of incomplete exchange rate pass through into import prices. In contrast, producers of commodities and low differentiation goods make minuscule or no adjustments. These different elasticities are mirrored (inversely) by cross market adjustments in quantities exported.

Altogether, these results tell us that the nature of the good matter enormously in gauging the extent of international market segmentation and firms’ market power across markets. A high degree of pricing-to-market can be expected for highly differentiated goods, for which the cross-market substitution of quantity by firms is very low. In contrast, firms producing low differentiation intermediates appear more similar to commodity producers, in their inconsequential use of destination-specific markup adjustments and their highly elastic cross-market substitution of supply.

This empirical evidence provides an important diagnostic for the development of open economy models featuring a richer and more detailed account of firms’ dynamics and strategies. We assess the extent to which leading models of export pricing and dynamics can account for the qualitative patterns and magnitudes of the elasticities we find in the data. Our (preliminary) results yield a sharp message: while leading models cannot match our evidence, a multi-country syncretic model—accounting for both multilateral competition among producers, and vertical interactions between exporters and local distributors—can.
References


\section{Theoretical Framework \[Preliminary and Incomplete\]}

The world consists of $H$ countries. In each country, there are two sectors, one selling goods that can be traded across countries and the other selling non-tradable goods such as services. There is a continuum of industries within the tradable sector. The elasticity of substitution across industries is \( \eta \). Each industry \( i \) processes goods with a natural degree of differentiation characterized by its within-industry elasticity of substitution \( \rho_i \) across varieties. The elasticity of substitution is strictly higher for varieties within an industry, \( \rho_i \), than cross industries, \( \eta < \rho_i \). There are \( M_i \) firms competing in each industry in an Atkeson and Burstein (2008) style. Further, we assume \( \chi_i \) units of non-tradable goods are needed to distribute a tradable product to the consumer as in Corsetti and Dedola (2005).\(^{38}\) Firms in the non-tradable sector are assumed to be monopolistically competitive. As we exploit destination variation to control for unobserved marginal costs, our model abstracts away from imported inputs.\(^{39}\)

Variables in this model have five dimensions with \( f, i, o, d, t \) standing for firm, industry, origin, destination, and time respectively. The tradable and non-tradable sectors are denoted with \( T \) and \( N \), respectively.

\subsection{Consumers}

There is a representative consumer in each destination \( d \) maximising his/her expected utility by choosing its optimal final consumption \( C_{d,t} \) and labour supply \( L_{d,t} \). As in Atkeson and Burstein (2008), we assume that the representative consumer can trade a complete set of international assets with its trade partners.

The representative consumer’s profit maximization problem is given as follows,

\[
\max_{C_{d,t},L_{d,t}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_{d,t}, L_{d,t})
\]

subject to

\[
U_{d,t} = \log[C_{d,t}^\kappa (1 - L_{d,t})^{1-\kappa}]
\]

\[
P_{d,t}C_{d,t} + \sum_o \left[ \sum_\nu p^B_{o,t}(\nu)B_{o,t}(\nu) - (1 + r_{o,t-1})B_{o,t-1} \right] e_{o,d,t} = W_{d,t}L_{d,t} + \Pi_{d,t}
\]

\(^{38}\)Vertical interactions between producers and distributors are also emphasized by Burstein, Eichenbaum and Rebelo (2005) and Burstein, Eichenbaum and Rebelo (2007) in relation to the transmission of large devaluations into local prices.

\(^{39}\)See recent discussions by e.g., Amiti, Itskhoki and Konings (2014) and Rodnyansky (2018).
where holding $B_{o,t}(\nu)$ will earn $B_{o,t}$ units of currency $o$ at $t+1$ if state $\nu$ happens. $p_{o,t}^B(\nu)$ is the price of a bond from origin $o$ with state $\nu$. $r_{o,t-1}$ represents the nominal interest rate paid in units of currency $o$ from $t-1$ to $t$. $\Pi_{d,t}$ is the lump-sum profit from all domestic firms and exporters in country $d$.

The solution of the representative consumer’s problem is given by

$$\frac{1 - \kappa}{\kappa} \frac{C_{d,t}}{1 - L_{d,t}} = W_{d,t} \frac{P_{d,t}}{P_{d,t}}$$

(13)

$$\frac{C_{o,t}P_{o,t}}{e_{o,t}C_{d,t}P_{d,t}} = \frac{C_{o,t+1}(\nu)P_{o,t+1}(\nu)}{e_{o,t+1}(\nu)C_{d,t+1}(\nu)P_{d,t+1}(\nu)}$$

(14)

where (13) represents the optimal division of consumption and labor and (14) stands for the conventional international risk sharing condition.

A.2 Firms

The final consumption is CES aggregated from tradable and non-tradable goods.

$$C_{d,t} = \left[ (C_{T,d,t})^{\frac{\theta-1}{\theta}} + (C_{N,d,t})^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$$

$$P_{d,t} = \left[ (P_{T,d,t})^{1-\theta} + (P_{N,d,t})^{1-\theta} \right]^{\frac{1}{1-\theta}}$$

(15)

where the elasticity of substitution between tradable and non-tradable goods is assumed to be $\theta$.

A.2.1 Non-tradable sector

The non-tradable sector is assumed to be monopolistically competitive. The equilibrium price and direct consumption of non-tradable goods can be derived as follows:

$$P_{N,d,t} = \frac{\theta}{\theta - 1} mc_{N,d,t}$$

(16)

$$C_{N,d,t} = \left( \frac{P_{N,d,t}}{P_{d,t}} \right)^{-\theta} C_{d,t}$$

(17)

Note that a part of non-tradable output is used for distribution purposes. Therefore, the total demand for non-tradable goods equals the direct consumption $C_{N,d,t}$ plus the amount used for distribution as characterized in (50).
A.2.2 Tradable sector

The demand for tradable goods can be derived as

\[ C_{T,d,t} = \left( \frac{P_{T,d,t}}{P_{d,t}} \right)^{-\theta} C_{d,t} \]  

(18)

The tradable goods, \( C_{T,d,t} \), are aggregated using a nested-CES function as in Atkeson and Burstein (2008). The consumption of tradable goods \( C_{T,d,t} \) in destination \( d \) is aggregated across sectors with a constant elasticity of substitution across industries equal to \( \eta \), i.e.,

\[ C_{T,d,t} \equiv \left[ \sum_i (C_{i,d,t})^{\frac{\eta-1}{\eta}} \right]^{\frac{1}{\eta}}, \quad P_{T,d,t} \equiv \left[ \sum_i (P_{i,d,t})^{1-\eta} \right]^{\frac{1}{1-\eta}} \]  

(19)

Within each industry, there are domestic and foreign firms producing different varieties with a constant elasticity of substitution \( \rho_i \). \( f \in 1_{i,o} \cap 1_E \) denotes foreign exporters in industry \( i \) from origin \( o \). \( f \in 1_{i,d} \) denotes domestic firms in industry \( i \). The industry-level consumption \( C_{i,d,t} \) and price \( P_{i,d,t} \) are given by:

\[ C_{i,d,t} \equiv \left[ \sum_{o \neq d} \sum_{f \in 1_{i,o} \cap 1_E} (q_{f,i,o,d,t})^{\frac{\rho_i-1}{\rho_i}} + \sum_{f \in 1_{i,d}} (q_{f,i,d,d,t})^{\frac{\rho_i-1}{\rho_i}} \right]^{\frac{1}{\rho_i-1}}, \]

\[ P_{i,d,t} \equiv \left[ \sum_{o \neq d} \sum_{f \in 1_{i,o} \cap 1_E} (p_{f,i,o,d,t})^{1-\rho_i} + \sum_{f \in 1_{i,d}} (p_{f,i,d,d,t})^{1-\rho_i} \right]^{\frac{1}{1-\rho_i}} \]  

(20)

A firm competes by choosing its price \( p_{f,i,o,d,t} \) internalizing its impact on the industry level price index \( P_{i,d,t} \):

\[ \max_{p_{f,i,o,d,t}} q_{f,i,o,d,t} \left[ (p_{f,i,o,d,t} - \chi_i P_{N,d,t}) e_{o,d,t} - m_{c,f,i,o,t} \right] \]

subject to

\[ q_{f,i,o,d,t} = \left( \frac{p_{f,i,o,d,t}}{P_{i,d,t}} \right)^{-\rho_i} \left( \frac{P_{i,d,t}}{P_{T,d,t}} \right)^{-\eta} C_{T,d,t} \]  

(21)

where \( m_{c,f,i,o,t} \) is the marginal cost of firm \( f \) from industry \( i \) and origin \( o \) at time \( t \); bilateral exchange rate \( e_{o,d,t} \) is defined as units of currency \( o \) per unit of currency \( d \) at time \( t \). We model vertical integration following Corsetti and Dedola (2005) and assume \( \chi_i \) units of destination nontradable goods are need to distribute the product to the consumer, resulting in an additional wedge, \( \chi_i P_{N,d,t} \).

\[ 40 \] In this nested CES structure, the main theoretical result is not sensitive to whether firms compete in prices or quantities. Atkeson and Burstein (2008) show that similar expressions can be derived if firms are competing in quantities.
in the profit maximisation problem.

A.2.3 Production Function

The production function is assumed to be linear in labour \( L \) and productivity \( \Omega \), i.e., \( Y = F(\Omega, L) \equiv \Omega L \). We assume wages are identical across sectors and industries. The marginal cost of a firm is calculated by dividing the nominal wage of the original country by the firm’s productivity, i.e.,

\[
m_{c,f,i,o,t} = \frac{W_{o,t}}{\Omega_{f,i,o,t}} \quad (22)
\]

\[
m_{c,N,d,t} = \frac{W_{d,t}}{\Omega_{N,d,t}} \quad (23)
\]

A.3 Price, Market Share and Demand Elasticity

The optimal consumer price \( p_{k,i,o,d,t} \) for exporter \( k \) from origin \( o \) to destination \( d \) denominated in the destination currency can be derived as

\[
p_{k,i,o,d,t} = \frac{\varepsilon_{k,i,o,d,t}(m_{s,k,i,o,d,t})}{\varepsilon_{k,i,o,d,t}(m_{s,k,i,o,d,t}) - 1} \left( \frac{m_{c,k,i,o,t}}{c_{o,d,t}} + \chi_i P_{N,d,t} \right) \quad (24)
\]

where \(-\varepsilon_{k,i,o,d,t}\) is the elasticity of demand with respect to consumer price; \( m_{c,k,i,o,t} \) is the marginal cost denominated in the exporter’s currency; and \( m_{s,k,i,o,d,t} \) is the market share of the exporter \( k \) in industry \( i \) of destination market \( d \) defined as

\[
m_{s,k,i,o,d,t} \equiv \frac{p_{k,i,o,d,t}q_{k,i,o,d,t}}{\sum_f p_{f,i,o,d,t}q_{f,i,o,d,t}} = \frac{p_{k,i,o,d,t}^{1-\rho_i}}{\sum_f (p_{f,i,o,d,t})^{1-\rho_i}}.
\]

Note that \( \varepsilon_{k,i,o,d,t} \) is not a constant but varies with the exporter’s market share. Specifically, under the assumption that the elasticity of substitution is higher within an industry than cross industries \((\rho_i > \eta)\), \( \varepsilon_{k,i,o,d,t} \) is a strictly decreasing function of market share, i.e., bigger firms face a less elastic demand and charge a higher markup.

\[
\varepsilon_{k,i,o,d,t} = (1 - m_{s,k,i,o,d,t})\rho_i + m_{s,k,i,o,d,t}\eta
\]

By log-linearizing equation (24), changes in price denominated in the exporter’s currency can be decomposed into changes in markups and marginal costs, i.e.,

\[
\hat{p}_{k,i,o,d,t} + \hat{e}_{o,d,t} = \kappa_{k,i,o,d,t}m_{s,k,i,o,d,t} - \omega_{k,i,o,d,t}(\hat{m}_{c,k,i,o,t} - \hat{e}_{o,d,t} - \hat{P}_{N,d,t}) + \hat{m}_{c,k,i,o,t} \quad (25)
\]

changes in markup \( \hat{p}_{k,i,o,d,t} \)
where \( \kappa_{k,i,o,d,t} \) is the price elasticity with respect to a firm’s own market share, which strictly decreases in the demand elasticity, \( \varepsilon_{k,i,o,d,t} \), and strictly increases in the exporter’s market share, \( m_{s,k,i,o,d,t} \), for a given set of within- and across-industry elasticities, \( \rho_i > \eta \),

\[
\kappa_{k,i,o,d,t} \equiv \frac{\rho_i - \varepsilon_{k,i,o,d,t}}{\left(\varepsilon_{k,i,o,d,t}\right)^2 - \varepsilon_{k,i,o,d,t}}
\]

and \( \omega_{k,i,o,d,t} \) represents the cost share of distribution,

\[
\omega_{k,i,o,d,t} \equiv \frac{\chi_i P_{N,d,t} e_{o,d,t}}{m_{c,k,i,o,t} + \chi_i P_{N,d,t} e_{o,d,t}}.
\]

The change in market share \( \hat{m}_{s,k,i,o,d,t} \) is given by (55) discussed later on in the text. Combining equations (55) and (25), we can obtain a general relationship for markup changes expressed in the exporter’s currency as

\[
\hat{\mu}_{k,i,o,d,t} = [1 - (1 - \lambda_{k,i,o,d,t})(1 - \omega_{k,i,o,d,t})] \left( \hat{e}_{o,d,t} - \hat{mc}_{k,i,o,t} \right) + \omega_{k,i,o,d,t} \left( \hat{P}_N,d,t - \kappa_{k,i,o,d,t} \hat{CE}_{k,i,o,d,t} \right)
\]

where \( (1 - \lambda_{k,i,o,d,t}) \) represents the incomplete pass through due to horizontal competition,

\[
\lambda_{k,i,o,d,t} \equiv 1 - \frac{1}{1 - (1 - m_{s,k,i,o,d,t})(1 - \rho_i)\kappa_{k,i,o,d,t}};
\]

\( (1 - \omega_{k,i,o,d,t}) \) represents incomplete pass through as a result of vertical integration due to the need to distribute products; and \( \hat{CE}_{k,i,o,d,t} \) is the total effect of competitors’ reactions,

\[
\hat{CE}_{k,i,o,d,t} = \sum_{o'} \sum_{f \neq k} m_{s,f,i,o',d,t}(1 - \rho_i) \left[ (1 - \omega_{f,i,o',d,t})(\hat{mc}_{f,i,o',d,t} - \hat{e}_{o',d,t}) + \omega_{f,i,o',d,t} \hat{P}_N,d,t + \kappa_{f,i,o',d,t} \hat{m}_{s,f,i,o',d,t} \right].
\]

The last expression shows that, in a multi-country economy, the optimal price response of an exporter is a function not only of own (origin-specific) exchange rate shock, but also of bilateral exchange rate shocks affecting all other trade partners, weighted by a non-linear function of competitors’ market share. We should note here that this extra channel is neglected by open macro theory, as the vast majority of models assume a two-country framework, and is not discussed in the original analysis of Atkeson and Burstein (2008). As shown by de Blas and Russ (2015), the changing distribution of markups in response to an aggregate shock could be quantitatively very different in a two-country versus three-country model with variable markups. We will show adding this component helps us reconcile our empirical estimates of the DSME and CMSE with the theoretical implied values.
The change in the border price, equal to the consumer price minus the distribution cost, i.e.,
\[ p_{b,k,i,o,d,t} \equiv p_{k,i,o,d,t} - \chi_i P_{N,d,t}, \]
is given by
\[
\hat{p}_{k,i,o,d,t} = \frac{1}{1 - d_{m,k,i,o,d,t}} \hat{p}_{k,i,o,d,t} - \frac{d_{m,k,i,o,d,t}}{1 - d_{m,k,i,o,d,t}} \hat{P}_{N,d,t}
\]
(28)
where the distribution margin \( d_{m,k,i,o,d,t} \) is defined as
\[
d_{m,k,i,o,d,t} \equiv \frac{\chi_i P_{N,d,t}}{p_{k,i,o,d,t}} = \omega_{k,i,o,d,t} \frac{\varepsilon_{k,i,o,d,t} - 1}{\varepsilon_{k,i,o,d,t}}
\]
(29)

Quantity responses can be derived from (21) as
\[
\hat{q}_{k,i,o,d,t} = -\varepsilon_{k,i,o,d,t} \hat{p}_{k,i,o,d,t} + \frac{\rho_i - \eta}{1 - \rho_i} \hat{C}_{E_{k,i,o,d,t}} + \eta \hat{P}_{T,d,t} + \hat{C}_{T,d,t}
\]
(30)

A.4 Relative price and quantity changes across destinations

In the following subsection, we discuss key properties of the model. In what follows, we refer to country 1 as the home economy and focus on the relative price and quantity responses of exporters in country 1 to destinations 2 and 3.
From (26), (28) and (30), we have

\[
\hat{p}_{k,i,1,2,t} + \hat{e}_{1,2,t} - (\hat{p}_{k,i,1,3,t} + \hat{e}_{1,3,t}) = \hat{\mu}_{k,i,1,2,t} - \hat{\mu}_{k,i,1,3,t}
\]

\[
= \begin{bmatrix}
\Gamma_{k,i,1,2,t}\hat{e}_{1,2,t} - \Gamma_{k,i,1,3,t}\hat{e}_{1,3,t} & \\
-(\Gamma_{k,i,1,2,t} - \Gamma_{k,i,1,3,t})\hat{m}c_{k,i,1,t} & \\
+(1 - \lambda_{k,i,1,2,t})\omega_{k,i,1,2,t}\hat{P}_{N,2,t} - (1 - \lambda_{k,i,1,3,t})\omega_{k,i,1,3,t}\hat{P}_{N,3,t} & \\
-(1 - \lambda_{k,i,1,2,t})\kappa_{k,i,1,2,t}\hat{C}\hat{E}_{k,i,1,2,t} + (1 - \lambda_{k,i,1,3,t})\kappa_{k,i,1,3,t}\hat{C}\hat{E}_{k,i,1,3,t}
\end{bmatrix}
\]

(31)

\[
\hat{p}_{k,i,1,2,t}^b + \hat{e}_{1,2,t} - (\hat{p}_{k,i,1,3,t}^b + \hat{e}_{1,3,t}) = \frac{\hat{\mu}_{k,i,1,2,t} - \hat{m}k_{i,1,2,t}(\hat{e}_{1,2,t} + \hat{P}_{N,2,t})}{1 - \hat{m}k_{i,1,2,t}} - \frac{\hat{\mu}_{k,i,1,3,t} - \hat{m}k_{i,1,3,t}(\hat{e}_{1,3,t} + \hat{P}_{N,3,t})}{1 - \hat{m}k_{i,1,3,t}}
\]

\[
= \begin{bmatrix}
\frac{\Gamma_{k,i,1,2,t} - \hat{m}k_{i,1,2,t}}{1 - \hat{m}k_{i,1,2,t}}\hat{e}_{1,2,t} - \frac{\Gamma_{k,i,1,3,t} - \hat{m}k_{i,1,3,t}}{1 - \hat{m}k_{i,1,3,t}}\hat{e}_{1,3,t} & \\
-(\frac{\Gamma_{k,i,1,2,t}}{1 - \hat{m}k_{i,1,2,t}} - \frac{\Gamma_{k,i,1,3,t}}{1 - \hat{m}k_{i,1,3,t}})\hat{m}c_{k,i,1,t} & \\
+(1 - \lambda_{k,i,1,2,t})\omega_{k,i,1,2,t}\hat{P}_{N,2,t} - (1 - \lambda_{k,i,1,3,t})\omega_{k,i,1,3,t}\hat{P}_{N,3,t} & \\
-(1 - \lambda_{k,i,1,2,t})\kappa_{k,i,1,2,t}\hat{C}\hat{E}_{k,i,1,2,t} + (1 - \lambda_{k,i,1,3,t})\kappa_{k,i,1,3,t}\hat{C}\hat{E}_{k,i,1,3,t}
\end{bmatrix}
\]

(32)

\[
\tilde{q}_{k,i,1,2,t} - \tilde{q}_{k,i,1,3,t} = \begin{bmatrix}
-\varepsilon_{k,i,1,2,t}\hat{p}_{k,i,1,2,t} - \varepsilon_{k,i,1,3,t}\hat{p}_{k,i,1,3,t} & \\
+\frac{\varepsilon_{k,i,1,2,t}}{\varepsilon_{k,i,1,2,t}}(\hat{C}\hat{E}_{k,i,1,2,t} - \hat{C}\hat{E}_{k,i,1,3,t}) & \\
+\eta(\hat{P}_{T,2,t} - \hat{P}_{T,3,t}) + \hat{C}_{T,2,t} - \hat{C}_{T,3,t}
\end{bmatrix}
\]

(33)

where

\[
\Gamma_{k,i,o,d,t} \equiv 1 - (1 - \lambda_{k,i,o,d,t})(1 - \omega_{k,i,o,d,t})
\]
Equation (31) states that the change in relative consumer prices at two different destinations (converted into the exporter’s currency) equals the change in relative markups across the two destinations. The latter in turn is decomposed in four terms, capturing, respectively, (i) the heterogeneous effect of changing marginal costs on markups, (ii) the relative movements in bilateral exchange rates, (iii) the relative change in non-tradable prices and (iv) the relative change in competition. Note that the relationship between these relative terms is governed by two key parameters, representing the degree of horizontal competition $\lambda_{k,i,1,2,t}$ and vertical integration $\omega_{k,i,1,2,t}$ respectively.

Equation (32) states that the change in relative border prices is governed by the same set of variables also included in (31), but the parameters are scaled up by the distribution margin at different locations—as the need for distributing products creates a wedge between consumer and border prices.

Equation (33) shows how quantities move across destinations. The change in relative quantities is a function of relative changes in the consumer price, weighted by the demand elasticity $\varepsilon_{k,i,o,d,t}$, the relative change in the degree of competition, and the relative change in demand for tradable goods.

A.4.1 A three-country case study

To gain analytical insight on how prices and quantities respond to changes in local conditions, we start with a symmetric case where firms in each country have similar productivity and thus market share distributions. The symmetric assumption helps to simplify our analysis by ensuring that $\varepsilon_{k,i,1,2,t} = \varepsilon_{k,i,1,3,t}$, $\lambda_{k,i,1,2,t} = \lambda_{k,i,1,3,t}$, $\omega_{k,i,1,2,t} = \omega_{k,i,1,3,t}$. As above, we focus on country 1 as the country of origin. For clarity, we will focus on trade in a generic industry $i$, dropping all unnecessary subscripts.

The following three equations show the evolution of prices (at the consumer level and at the border, respectively) and quantities.

\[
\hat{p}_2 + \hat{e}_2 - (\hat{p}_3 + \hat{e}_3) = \Gamma(\hat{e}_2 - \hat{e}_3) + (1 - \lambda)\omega(\hat{P}_{N,2} - \hat{P}_{N,3}) - (1 - \lambda)\kappa(C\bar{E}_2 - C\bar{E}_3) \tag{34}
\]

\[
\hat{p}_2^b + \hat{e}_2 - (\hat{p}_3^b + \hat{e}_3) = \frac{\Gamma}{1 - dm}(\hat{e}_2 - \hat{e}_3) + \frac{(1 - \lambda)\omega}{1 - dm}(\hat{P}_{N,2} - \hat{P}_{N,3}) - \frac{(1 - \lambda)\kappa}{1 - dm}(C\bar{E}_2 - C\bar{E}_3) \tag{35}
\]

\[
\hat{q}_2 - \hat{q}_3 = -\varepsilon(\hat{p}_2 - \hat{p}_3) + \frac{\rho - \eta}{1 - \rho}(C\bar{E}_2 - C\bar{E}_3) + \eta(\hat{P}_{T,2} - \hat{P}_{T,3}) + \hat{C}_{T,2} - \hat{C}_{T,3} \tag{36}
\]

From these three equations, we can see that the direct effect of relative changes in exchange rates on the consumer price is given by $\Gamma$, reflecting strategic complementaries due to horizontal competition and vertical interactions. The responsiveness of border prices, however, is dampened...
by the wedge induced by the need for distribution services, resulting in an overall elasticity given by $\Gamma_{\frac{-dm}{1-dm}}$.

Rearranging (36), we get

$$\hat{q}_2 - \hat{q}_3 = -\varepsilon(\Gamma - 1)(\hat{e}_2 - \hat{e}_3) - \varepsilon(1 - \lambda)\hat{\omega}(\hat{P}_{N,2} - \hat{P}_{N,3}) + \left[\frac{\rho - \eta}{1 - \rho} + \varepsilon(1 - \lambda)\kappa\right](\hat{C}_E_2 - \hat{C}_E_3)$$

$$+ \eta(\hat{P}_{T,2} - \hat{P}_{T,3}) + \hat{C}_{T,2} - \hat{C}_{T,3}$$

(37)

Since changes in relative quantities are a function of changes in relative prices, in turn a function of relative exchange rate movements, the coefficient on the latter is also a function of $\Gamma$—that is, $-\varepsilon(\Gamma - 1)$.

Before we can relate these expressions to our estimators, we need to work more on the term capturing multilateral competitive effects ($\hat{C}_E_2 - \hat{C}_E_3$), which, as suggested by (27), is a complex function of bilateral exchange rates. Unfortunately, with firms competing in an Atkeson and Burstein (2008) style, there is no closed form solution for (27). We can nonetheless think of it as an unknown function $G$ of relative changes in exchange rates, $\hat{e}_2 - \hat{e}_3$, and other factors, uncorrelated with the relative change in bilateral exchange rates—to be approximated linearly as follows:

$$(1 - \lambda)\kappa(\hat{C}_E_2 - \hat{C}_E_3) = G(\hat{e}_2 - \hat{e}_3, \hat{O}_2 - \hat{O}_3) \approx a \cdot (\hat{e}_2 - \hat{e}_3) + O(\hat{O}_2 - \hat{O}_3)$$

(38)

In general, $a$ will reflect the multilateral effects of destination-specific changes in local conditions. Intuitively, altering the economic environment in country B would simultaneously affect exporters in country A and country C—exporters from both A and C receive shocks of a similar magnitude. In terms of exchange rates, the depreciation of country B’s currency would simultaneously affect the bilateral exchange rates between A and B as well as between C and B.

By virtue of the approximation above, equations (35) and (37) map into our estimators as follows:

Destination Specific Markup Elasticity $\approx \frac{\Gamma - dm - a}{1 - dm}$

Cross Market Supply Elasticity $\approx \frac{[-\varepsilon(\Gamma - 1) + b \cdot a]}{DSME}$

(39) (40)

where $b$ captures the quantity multiplier of the multilateral effect—which can be derived as

$$b \equiv \frac{1}{\kappa(1 - \lambda)} \frac{\rho - \eta}{1 - \rho} + \varepsilon$$

(41)

Using the expressions for $\lambda$ and $\varepsilon$, we can finally rewrite the equations (39) and (40) to get...
analytical solutions in terms of $\eta, \rho, \omega$, the multilateral effect $a$ and market shares $ms$.

$$\varepsilon = (1 - ms)\rho + ms \cdot \eta$$

$$\lambda = \frac{ms(1 - ms)}{\rho - \eta - \frac{\rho - 1}{\rho - 1} ms^2}$$

$$b = \frac{\rho(2\rho - \eta - 1)}{\rho - 1} - \frac{\rho}{ms} - \frac{(\rho - \eta)^2}{\rho - 1} ms$$

$$DSME = 1 - \left[ (1 - \lambda)(1 - \omega) + a \right] \cdot \frac{\varepsilon}{\varepsilon(1 - \omega) + \omega}$$

$$CMSE = \left[ \varepsilon(1 - \lambda)(1 - \omega) + b \cdot a \right] / DSME$$

We deal with the unobserved $a$ using different methods. According to one method, we fix the value of some analytical parameters, and search for possible values of $a$ that fit our empirical estimates. For example, for given values of $\rho, \eta$ and $ms$, we can find parameter values of $\omega$ and $a$ that minimize the distance between empirical elasticities and model suggested values. Results are discussed in table (9).

As an alternative solution, we approximate $a$ as

$$a \approx 0.99(1 - \lambda)\kappa(1 - ms)(\rho - 1)(1 - \omega)$$

Note that $(\rho - 1)(1 - \omega)$ is the coefficient in front of the bilateral exchange rates in equation (27). $(1 - \lambda)\kappa$ is the coefficient in front of the total effect of competitors’ reactions as can be seen in (26). In general, the values of $\gamma, \kappa$ and $\omega$ could be firm specific. In this approximation, we implicitly assume that they are identical across firms. We discuss in greater detail how we construct our approximation in Section A.6.2.

**A.4.2 Theoretical DSME and CMSE: an analytical discussion of the determinants of these elasticities**

In this subsection, we analyze the elasticities (DSMEs and CMSEs) predicted by our model, and assess their sensitivity to varying $\omega, \rho, \eta, ms$ and $a$. One advantage of our specification is that we can isolate the effect of different mechanisms and market structures in a modular way. In particular, by setting $\omega$ to 0, we obtain a model close to Atkeson and Burstein (2008), henceforth AB. By setting $ms$ to 0, we obtain a model close to Corsetti and Dedola (2005), henceforth CD. For intermediate cases, we can study the results integrating the two models. Another advantage is that we can provide a transparent analytical discussion of which parameters is crucial for our model to bring the theoretical elasticities in line with our empirical results.

In what follows, we will illustrate the properties of the model by conducting a number of
case studies. In the first four cases, we will abstract from the multilateral effect, restricting \( a \) to be identically equal to 0. We will then turn to the analysis of the full model, integrating all the building blocks and analyze their interaction. To be consistent with our empirical results, throughout our analysis we will report markups measured in the exporter’s currency.

**Case 1: Only Horizontal Competition, AB**

\[
\Gamma = 1 - (1 - \lambda)(1 - \omega)
\]

Note: Fixed Parameters: \( \omega = 0, \eta = 2 \)

**Destination Specific Markup Elasticity** (at border price)

Note: Fixed Parameters: \( \omega = 0, \eta = 2 \)

**Cross Market Supply Elasticity**

Note: Fixed Parameters: \( \omega = 0, \eta = 2 \)
In Case 1, in addition to abstracting from multilateral competition effects (by setting \( a = 0 \)), we abstract from vertical interactions (by setting \( \omega = 0 \)). This means that we can focus on a specification close to the original model by Atkeson and Burstein (2008). With no vertical integration (\( \omega = 0 \)), the destination-specific markup adjustment is the same at the border and at the consumer price level. Both are driven by competition among producers of substitute goods—‘horizontal competition’ for short. Incomplete pass through is driven by the degree of horizontal competition, indexed by \( \lambda \).

The four panels in Case 1 plot, respectively, \( \lambda \), \( \Gamma \), DSME and CMSE predicted by the model, against the firm’s market share—keeping the cross-industry elasticity of substitution, \( \eta \), fixed at 2. Note that the lower panel on the left-hand-side reproduces the well-known AB result, that markup adjustments are non-linear in market share—hump-shaped when markups are measured in domestic currency, U-shaped if markups are measured in the destination currency.

To explore the role of the elasticity of substitution, \( \rho \), each panel plots two lines, one for a high value and one for a low value of \( \rho \). A higher (lower) \( \rho \) represents a less (more) differentiated industry where the degree of substitution among varieties is high (low). The results from this specification of the model are strikingly at odds with our empirical estimates of the DSME: as
shown by the lower panel on the left-hand-side, the model predicts a lower destination-specific markup adjustment (measured in the exporter’s currency) for more differentiated products. In our empirical section, we have seen that the DSME is always higher for more differentiated products. The picture is less clear-cut concerning the CMSE, whereas the two lines cross each other for values of $ms$ around 0.5.

Looking at the magnitude of these elasticities, the range of the theoretical DSME appears in line with our empirical estimates. However, the theoretical CMSE is too high relative to our empirical counterparts. In fact, as will be shown below, there is no numerical solution that can simultaneously match our empirically estimated DSMEs and CMSEs by varying $\rho, \eta, ms$ while keeping $\omega = 0$ and $a = 0$ fixed.

Case 2: Only Vertical Integration, CD

\begin{align*}
\Gamma &= 1 - (1 - \lambda)(1 - \omega) \\
\text{Note: Fixed Parameters: } ms \to 0
\end{align*}

In Case 2, instead, we abstract from the horizontal competition highlighted by AB. We do so by setting the market share of exporters to zero, i.e., $ms \to 0$. By virtue of this assumption, the model simplifies to a CES demand case where, if $\omega$ were zero, the elasticity of substitution among varieties would be equal to $\rho$.

For a nonzero $\omega$, Case 2 allows us to study a model close to Corsetti and Dedola (2005). In
CD, vertical interactions between producers and distributors drive a wedge between prices at the border and at the consumer level—implying that, for a given within-sector elasticity of substitution $\rho$, the demand elasticity with respect to the border price is a strictly decreasing function of the distribution margin, $dm$, in turn a linear function of the level of vertical integration, $\omega$.

If $ms \to 0$ and $a = 0$, the expression (45) can be simplified as follows:

$$DSME = \frac{1}{\rho(1/\omega - 1) + 1}$$

The markup elasticity with respect to the border price denominated in the exporters’ currency, DSME, is a strictly increasing function of the level of vertical interaction, $\omega$. Intuitively, keeping the within-industry elasticity of substitution, $\rho$, fixed, a higher $\omega$ is associated with a larger distribution margin, causing the demand for the product to be less elastic with respect to the border price. Correspondingly, a higher level of vertical interaction, $\omega$, monotonically decreases CMSE. At the same time, however, DSME is a strictly decreasing function—and CMSE a strictly increasing function—of the within-industry elasticity of substitution, $\rho$.

The four panels in the figure plot the predicted $dm$, $\Gamma$, DSME and CMSE against the degree of vertical interactions, indexed by $\omega$, for this case. The model predicts that the DSME is higher (i.e., markup adjustment is larger) for low elasticity (highly differentiated) goods—with quantity adjustments going in the opposite directions. Qualitatively, thus, the model with only vertical interactions appears to be consistent with our estimates of DSME and CMSE for products with different level of differentiation. However, the model does not square well quantitatively: the CMSE is too high.

In concluding the discussion of this case, note that the markup elasticity with respect to the consumer price, $\Gamma$, moves one-to-one with the level of vertical integration, $\omega$, independent of $\rho$ (see the panel on the upper right hand side).
Case 3: Incorporating both Horizontal and Vertical Interactions, ABCD

Case 3 shows that combining both horizontal and vertical interactions (while still keeping $a = 0$) helps in lowering the magnitude of the theoretical CMSE closer to our empirical estimates. The panels are the same as in Case 1, but the plots are now conditional on setting $\omega = .5$.

Most importantly, the lower panel on the left-hand-side shows that both vertical and horizontal interactions impinge on the relationship between DSME and product differentiation (the value of $\rho$). With the cost share of the local component $\omega$ set equals 0.5, DSME is increasing in the level of differentiation (a lower $\rho$) when the firm’s market share is small, but decreasing in the level of
differentiation when the firm’s market share is large. We characterize this relationship in further
detail in the case to follow.

Case 4: Comparing the Effect of Horizontal and Vertical Components

In Case 4, we carry out a comparative analysis of AB and CD, contrasting horizontal and
vertical interactions. The panels plot the theoretically predicted $\lambda$, $\Gamma$, the $DSME$ at the border,
the $CMSE$ and the distribution margin against the within-industry elasticity of substitution, $\rho$.
Solid lines refer to the same model as in case 1, broken lines as in case 3.

With only horizontal competition (solid black line), the degree of horizontal competition, $\lambda$, is
strictly increasing in the within-industry elasticity of substitution, $\rho$. In this case,

$$DSME = \lambda \quad \text{and} \quad CMSE = \varepsilon(1/\lambda - 1) \quad (49)$$

When $\rho$ approaches $\eta$ (set equal to 2), the effect of horizontal competition is very small and the markup adjustments are close to zero. At this point, since the quantity differences across markets approach the elasticity of substitution $\eta$, the CMSE goes to infinity. With higher values of $\rho$, the cross-market markup differences rise at a faster speed compared to cross-market quantity differences. As a result, CMSE is decreasing in $\rho$.

With only vertical interactions (dashed blue line), a higher $\rho$ means a lower markup in the final consumer price\textsuperscript{41}. Everything else equal, the cost of the local nontraded input constitutes a larger fraction of the final consumer price—which thus becomes more insulated from shocks like tariffs or exchange rates that hit the border price. Because of the insulating effect of a larger distribution margin, movements in the border price have less influence on final demand: the border price/markup denominated in the local currency reacts more to changes in exchange rates and tariffs (whereas the border price/markup denominated in the exporter’s currency reacts less).

The implications for the CMSE of different $\rho$ can be understood as the result of two opposing forces explained above. With a higher $\rho$, on the one hand, demand is more elastic because products are more substitutable ($\rho$ is higher). On the other hand, demand becomes less elastic with respect to the border price, because, everything else equal, the distribution margin is higher. The panel suggests that the latter channel dominates for increasing values of $\rho$.

\textsuperscript{41}The markup in the consumer price is defined as the consumer price divided by the total cost denominated in the local currency, where the total cost includes the marginal cost of production of the exporter converted to the local currency plus the local cost of production and distribution.
Table 9: Incorporating Multilateral Effects, $ABCD^H$
Numerical Solutions: to target evidence, solving for parameters

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Targets</th>
<th>DSME</th>
<th>CMSE</th>
<th>Status</th>
<th>Residual</th>
<th>$ms$</th>
<th>$\eta$</th>
<th>$\rho$</th>
<th>$\omega$</th>
<th>$a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Changing $\eta \in (1.01, 2)$, $\rho \in (2, 20)$, and $a \in (0, 1)$ with $ms = 0.2$ and $\omega = 0.5$</td>
<td></td>
<td>0.20</td>
<td>0.83</td>
<td>Solved</td>
<td>0.00</td>
<td>0.20</td>
<td>1.22</td>
<td>3.16</td>
<td>0.50</td>
<td>0.10</td>
</tr>
<tr>
<td>Changing $\omega \in (0, 1)$ and $a \in (0, 1)$ with $ms = 0.2$, $\eta = 2$ and $\rho = 8$</td>
<td></td>
<td>0.20</td>
<td>0.83</td>
<td>Solved</td>
<td>0.00</td>
<td>0.20</td>
<td>2.00</td>
<td>8.00</td>
<td>0.69</td>
<td>0.06</td>
</tr>
<tr>
<td>Changing $\eta \in (1.01, 2)$, $\rho \in (2, 20)$, $ms \in (0, 1)$, and $\omega \in (0, 1)$ with $a = 0$</td>
<td></td>
<td>0.20</td>
<td>0.83</td>
<td>Infeasible</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>
Table 9 reports our core results. In the table, the second and third columns report the empirical estimates to be matched. The last five columns list the values of the market share $ms$, the cross-industry elasticity of substitution $\eta$, the within-industry elasticity of substitution $\rho$, the degree of vertical integration $\omega$, and the multilateral effect $a$, for which the model matches our elasticities. The third column indicates whether we can solve the model for values of $ms$ in the ranges specified in the first column.

The table shows the results from three exercises. In the first exercise, we fix $ms$ and $\omega$, and solve for $\eta$, $\rho$, and $a$ to match our empirical estimates. As apparent from the table, as the markup elasticity (DSME) becomes smaller, the elasticities of substitution become larger, meaning that products are more substitutable with one another. There is no appreciable change in $a$.

In the second exercise, we fix the elasticities of substitution ($\eta, \rho$) and let the level of vertical integration $\omega$ vary. As the markup elasticity becomes smaller, the fitted value of $\omega$ becomes smaller, suggesting a smaller proportion of local components.

The third exercise shows that, to match the magnitude and patterns of the empirical results, the multilateral effects cannot be shut down. If we set the multilateral effect $a$ to zero, the model is no longer able to match our empirical estimates.
The following two figures show additional results concerning the role of multilateral competition effects.

Incorporating Multilateral Effects: $ABCD^H$
Changing Market Share

Degree of Horizontal Competition, $\lambda$

$\Gamma = 1 - (1 - \lambda)(1 - \omega)$

Multilateral Effect, $a$

Distribution Margin

Destination Specific Markup Elasticity
(at border price)

Cross Market Supply Elasticity

Note: Fixed Parameters: $\omega = .5$, $\eta = 2$
Incorporating Multilateral Effects: $ABCD^H$
Changing the Level of Vertical Integration

Degree of Horizontal Competition, $\lambda$

$\Gamma = 1 - (1 - \lambda)(1 - \omega)$

Multilateral Effect, $a$

Distribution Margin

Destination Specific Markup Elasticity (at border price)

Cross Market Supply Elasticity

Note: Fixed Parameters: $ms = .2$, $\eta = 2$
A.5 Equilibrium conditions

The competitive equilibrium is characterized as follows.

1. The representative consumer in each country chooses consumption, labour supply and optimal international bond holding to maximize its expected utility as in (13) and (14).

2. Firms in each country set prices to optimize their profits given their marginal cost as in (22) and (23). The optimal prices are given by (16) and (24).

3. Markets clear. This involves the aggregation conditions (15), (18), (19), (20) and (21) together with other market clearing conditions listed below.

Total demand for non-tradable goods is given by

\[ q_{N,d,t} = C_{N,d,t} + \sum_i \chi_i \left[ \sum_{o \neq d} \sum_{f \in 1_i, o \cap \mathcal{E}} q_{f,i,o,d,t} + \sum_{f \in 1_i,d} q_{f,i,d,d,t} \right] \tag{50} \]

For each firm, the total quantity of products sold equals the quantity produced.

\[ \Omega_{f,i,o,t} l_{f,i,o,t} = \sum_d q_{f,i,o,d,t} \tag{51} \]

\[ \Omega_{N,o,t} L_{N,o,t} = q_{N,o,t} \tag{52} \]

The labor market clears:

\[ \sum_{f,i} l_{f,i,o,t} + L_{N,o,t} = L_{o,t} \tag{53} \]

The bilateral trade balance between \( o \) and \( d \) is given by (financial autarky case):

\[ \sum_{f,i} (p_{f,i,d,o,t} - \chi_i P_{N,d,t}) q_{f,i,d,o,t} = \sum_{f,i} (p_{f,i,d,o,t} - \chi_i P_{N,o,t}) q_{f,i,o,d,t} * e_{o,d,t} \quad \text{for} \ o \neq d \tag{54} \]

The nominal wage \( W_{o,t} \) in each origin is set as the numeraire. In this model, the productivity distribution can be asymmetric across industries, sectors and countries. As a result, the bilateral nominal exchange rate is not necessarily equal to one. Under the financial autarky case, the steady state bilateral exchange rate is determined by the bilateral balance of trade condition.
A.6 Solutions

A.6.1 Solution for market shares

Note that both $\hat{\mu}_{k,i,o,d,t}$ and $\hat{e}_{o,d,t}$ are state variables and exogenous to firms. After a shock, firms adjust their optimal prices and reach a new equilibrium. The deviation of market share $\hat{m}_{k,i,o,d,t}$ for firm $k$ in the new equilibrium compared to the old one depends on the ex ante market structure, i.e., market share distributions $\{m_{k,i,o,d,t}\}_{k \in 1_f,o' \in 1_o}$, marginal cost shocks to its competitors $\{\hat{\mu}_{k,i,o,d,t}\}_{k \in 1_f,o' \in 1_o}$, and the bilateral exchange rate movements of all trade partners of country $d$, $\{\hat{e}_{o',d,t}\}_{o' \in 1_o}$.

\[
\hat{m}_{k,i,o,d,t}[1 - (1 - \hat{m}_{k,i,o,d,t})(1 - \rho_i)\kappa_{k,i,o,d,t}] \\
= (1 - \hat{m}_{k,i,o,d,t}) \left\{ (1 - \rho_i) \left[ (1 - \omega_{f,i,o,d,t})(\hat{\mu}_{k,i,o,d,t} - \hat{e}_{o,d,t}) + \omega_{f,i,o,d,t}\hat{P}_{N,d,t} \right] \right\} \\
- \sum_{o'} \sum_{f \neq k} m_{f,i,o',d,t}[1 - (1 - \omega_{f,i,o',d,t})(\hat{\mu}_{f,i,o',d,t} - \hat{e}_{o',d,t}) + \omega_{f,i,o',d,t}\hat{P}_{N,d,t} + \kappa_{f,i,o',d,t}\hat{m}_{f,i,o',d,t}] \right\}
\]

Equation (55) states that the importance of competitors’ reactions depend on the elasticity of substitution within industries, $\rho_i$, and the market share of its competitors, $\hat{m}_{k,i,o,d,t}$.

It is worth stressing that even under a firm specific shock, the equilibrium effect of changing market shares for other firms $\sum_{o'} \sum_{f \neq k} m_{f,i,o',d,t}\kappa_{f,i,o',d,t}\hat{m}_{f,i,o',d,t}$ will not be zero in most cases. Note that the expression $\kappa_{f,i,o',d,t}$ is strictly increasing in market share $m_{f,i,o',d,t}$. That is, the importance of the changing market share of a competitor to firm $f$ is strictly increasing in the market share of that competitor.

Under the presence of $\hat{m}_{f,i,o',d,t}$, there is no simple analytical solution for the change in market share after a shock even under the first order approximation. Given a set of realised shocks and a prior market structure distribution, market share conditions will formulate a system of $M_i$ nonlinear equations that can be solved numerically.

A.6.2 Approximating for competitors’ reactions, $\hat{CE}$

To gain insights, we now solve equation (55) under the case where firms are ex ante identical after adjusting for exchange rate differences within industry $i$ and destination $d$. That is, we analyse the case that

$$\frac{mc_{k,i,o',t}}{e_{o',d,t}} = \frac{mc_{f,i,o,t}}{e_{o,d,t}} \forall k \in 1_f, o' \in 1_o$$

This condition implies the same market share $m_{k,i,o,d,t}$, share of distribution cost $\omega_{f,i,o,d,t}$, price elasticity with respect to market share $\kappa_{k,i,o,d,t}$, and the degree of horizontal competition $\lambda_{k,i,o,d,t}$.
across firms. We drop all unnecessary subscripts for clarity.

\[
\hat{m}_{k,o} [1 - (1 - ms)(1 - \rho)\kappa] = (1 - ms)(1 - \rho) \left[ (1 - \omega)(\hat{mc}_{k,o} - \hat{e}_o) + \omega \hat{P}_N \right] \\
- ms(1 - \rho) \sum_{o'} \sum_{f \neq k} \left[ (1 - \omega)(\hat{mc}_{k,o'} - \hat{e}_{o'}) + \omega \hat{P}_N + \kappa \hat{m}_{f,o'} \right]
\]

Note that \(\sum_{o'} \sum_{f \neq k} \hat{m}_{f,o'} = -\hat{m}_{k,o} \). Rearrange and get

\[
\hat{m}_{k,o} = \frac{(1 - \lambda)(1 - \rho)(1 - ms)}{1 - \kappa(1 - \lambda)(1 - \rho) ms} \left[ (1 - \omega)(\hat{mc}_{k,o} - \hat{e}_o) + \omega \hat{P}_N \right] \\
- \frac{(1 - \lambda)(1 - \rho)ms}{1 - \kappa(1 - \lambda)(1 - \rho) ms} \sum_{o'} \sum_{f \neq k} \left[ (1 - \omega)(\hat{mc}_{f,o'} - \hat{e}_{o'}) + \omega \hat{P}_N \right]
\]

Define \(\Upsilon \equiv \kappa(1 - \lambda)(1 - \rho)ms \). We can write

\[
\kappa \hat{m}_{k,o} = \frac{1 - ms}{ms} \left[ (1 - \omega)(\hat{mc}_{k,o} - \hat{e}_o) + \omega \hat{P}_N \right] \Upsilon \left( 1 + \frac{\Upsilon}{1 - \Upsilon} \right) \\
- \sum_{o'} \sum_{f \neq k} \left[ (1 - \omega)(\hat{mc}_{f,o'} - \hat{e}_{o'}) + \omega \hat{P}_N \right] \Upsilon \left( 1 + \frac{\Upsilon}{1 - \Upsilon} \right)
\]

The change in markup denominated in the exporter’s currency can be written as

\[
\hat{\mu}_{k,o} = [1 - (1 - \lambda)(1 - \omega)] (\hat{e}_o - \hat{mc}_{k,o}) + (1 - \lambda)\omega \hat{P}_N \\
- \Upsilon \sum_{o'} \sum_{f \neq k} \left[ (1 - \omega)(\hat{mc}_{f,o'} - \hat{e}_{o'}) + \omega \hat{P}_N \right] \\
+ \frac{1 - ms}{ms} \frac{\Upsilon}{1 - \Upsilon} \left[ (1 - \omega)(\hat{mc}_{k,o} - \hat{e}_o) + \omega \hat{P}_N \right] \\
- \frac{\Upsilon^2}{1 - \Upsilon} \sum_{o'} \sum_{f \neq k} \left[ (1 - \omega)(\hat{mc}_{f,o'} - \hat{e}_{o'}) + \omega \hat{P}_N \right]
\]

The first line represents the direct effect of shocks. The second line reflects how the competitors’ reactions to these shocks would directly affect the optimal markup of exporter \(k\). The third and fourth lines represent the indirect effects of changing competitors’ market shares.

Consider the case where the destination country depreciates against all of its trade partners. That is, \(\hat{e}_{o'} = \hat{e}_o \forall o \neq d \) and \(\hat{e}_d = 0\). For clarity, we also keep the marginal cost of all firms fixed...
and assume the price of non-tradable goods does not change in the destination.

\[
\hat{\mu}_{k,o} = [1 - (1 - \lambda)(1 - \omega)]\hat{e}_o + \Theta \frac{1 - ms}{ms} \Upsilon (1 - \omega)\hat{e}_o
\]

\[
- \frac{1 - ms}{ms} \frac{\Upsilon}{1 - \Upsilon} (1 - \omega)\hat{e}_o + \Theta \frac{1 - ms}{ms} \frac{\Upsilon^2}{1 - \Upsilon} (1 - \omega)\hat{e}_o
\]

\[
= [1 - (1 - \lambda)(1 - \omega)]\hat{e}_o - \kappa (1 - \lambda)C\hat{E}_{k,o}
\]

Where \( \Theta \) is the proportion of domestic firms in the residual market of industry \( i \) at destination \( d \). In a symmetric setup, \( \Theta \) is the number of domestic firms divided by the total number of firms in industry \( i \) minus one, i.e., \( \frac{M_d}{M - 1} \). The last three terms of equation (56) represent the total effect of competitors’ reactions, which can be written as

\[
\kappa (1 - \lambda)C\hat{E}_{k,o} = \frac{1 - ms}{ms} \Upsilon (1 - \omega)\hat{e}_o \left( \frac{1 - \Theta}{1 - \Upsilon} \right)
\]

\[
= (1 - \omega)(1 - \lambda)\kappa (\rho - 1)(1 - ms)\hat{e}_o \left( \frac{1 - \Theta}{1 - \Upsilon} \right)
\]

\[
\approx c \cdot (1 - \omega)(1 - \lambda)\kappa (\rho - 1)(1 - ms)\hat{e}_o
\]

where \( c \) is a constant and expression (57) gives our approximation equation (47). Note that, in a general case without the symmetric assumption, \( \Theta \) is likely to be an increasing function of market share of foreign firm \( k \). For a set of domestic firms with a given output, the presence of a foreign firm \( k \) with a larger market share implies the residual market to be split among all domestic firms is smaller, which, in turn indicates a greater market share of domestic firms in the residual market. This make it inappropriate to fix \( \Theta \) as a parameter. However, note that \( \Upsilon \) is also an increasing function of market share, i.e.,

\[
\frac{\partial \Upsilon}{\partial ms} = \Upsilon^2 \rho \left[ \frac{\rho (1 - ms) + \eta ms - 1}{ms^2 (\rho - 1)(\rho - \eta)} \right] > 0
\]

In our approximation (47), we have assumed a simple proportional relationship between \( 1 - \Theta \) and \( 1 - \Upsilon \) and fixed \( c \) to 0.99.
A.6.3 Solution for $a$, $b$, $\kappa$ and $\lambda$

Collect equations

\begin{align*}
\lambda &= 1 - \frac{1}{1 - (1 - ms)(1 - \rho)\kappa} \\
\kappa &= \frac{\rho - \varepsilon}{\varepsilon^2 - \varepsilon} \\
\varepsilon &= (1 - ms)\rho + ms \cdot \eta
\end{align*}

Rearrange and get

\begin{align*}
a &\approx (1 - \omega)(1 - \lambda)\kappa(\rho - 1)(1 - ms) \\
&= (1 - \omega) \cdot \frac{1}{\kappa(\rho - 1)(1 - ms)} + 1 \\
&= (1 - \omega) \cdot \frac{1}{\frac{\varepsilon(\varepsilon - 1)}{(\rho - \eta)ms(1 - ms)}} + 1 \\
&= (1 - \omega) \cdot \frac{1}{\frac{(\rho - 1)(\rho - \eta)ms(1 - ms)}{\rho(\rho - 1) - \rho(\rho - \eta)ms + (1 - \eta)(\rho - \eta)ms^2}} \\
&= (1 - \omega) \cdot \frac{\rho}{\rho - \eta} - \frac{\rho}{\rho - 1}ms - \frac{\eta - 1}{\rho - 1}ms^2
\end{align*}

\begin{align*}
b &= \frac{1}{\kappa(1 - \lambda)} \frac{\rho - \eta}{1 - \rho} + \varepsilon \\
&= \left[ 1 - (1 - ms)(1 - \rho) \right] \frac{\rho - \eta}{1 - \rho} + \varepsilon \\
&= \left[ \frac{\varepsilon(\varepsilon - 1)}{(\rho - \eta)ms} - (1 - ms)(1 - \rho) \right] \frac{\rho - \eta}{1 - \rho} + \varepsilon \\
&= \frac{\varepsilon(\varepsilon - 1)}{ms(1 - \rho)} - (1 - ms)(\rho - \eta) + \varepsilon \\
&= \frac{\varepsilon(\varepsilon - 1)}{ms(1 - \rho)} + \eta \\
&= - [\rho + (\eta - \rho)ms] \left[ \frac{1}{ms} + \frac{\eta - \rho}{\rho - 1} \right] + \eta \\
&= \frac{\rho(2\rho - \eta - 1)}{\rho - 1} - \frac{\rho}{ms} - \frac{(\rho - \eta)^2}{ms}
\end{align*}
\[
\lambda = 1 - \frac{-ms(1 - ms)(\rho - \eta) + (1 - \rho - \eta)ms + \frac{\rho(\rho-1)}{\rho-\eta}}{-ms(1 - ms)(1 - \eta) + (1 - \rho - \eta)ms + \frac{\rho(\rho-1)}{\rho-\eta}}
\]

\[
= \frac{ms(1 - ms)}{\frac{\rho}{\rho-\eta} - \frac{\rho}{\rho-1}ms + \frac{\eta-1}{\rho-1}ms^2}
\] (59)

B General Relationships (Model Free)

B.1 Derivation on the separation of marginal cost and markup components

Please note that variables in the following derivation are presented in levels rather than logarithms.

\[
\max_p q(p, \xi) p - c[q(p, \xi), \zeta]
\] (60)

The firm takes its demand function, \(q(p, \xi)\), and cost function, \(c[q(p, \xi), \zeta]\), as given and maximises its profit by choosing its optimal price \(p\). \(\xi\) and \(\zeta\) are exogenous demand and supply function shifters respectively.

The first order condition of the firm is given by

\[
\frac{\partial q(p, \xi)}{\partial p} p + q(p, \xi) = \frac{\partial c[q(p, \xi), \zeta]}{\partial q(p, \xi)} \frac{\partial q(p, \xi)}{\partial p}
\] (61)

From this equation, we can derive the optimal price as

\[
p^* = \frac{\varepsilon(p^*, \xi)}{\varepsilon(p^*, \xi) - 1} mc[q(p^*, \xi), \zeta]
\] (62)

where \(\varepsilon(p, \xi) \equiv -\frac{\partial q(p, \xi)}{\partial p} \frac{p}{q(p, \xi)},\ mc[q(p, \xi), \zeta] \equiv \frac{\partial c[q(p, \xi), \zeta]}{\partial q(p, \xi)}\).

B.2 The equilibrium relationship between quantity and price under pure supply versus demand shocks

**Proposition 1.** If changes in price and demand are solely driven by shocks to the supply side, the following expression holds

\[
\frac{d \log(q^*)}{d \log(p^*)} = -\varepsilon(p^*, \xi)
\] (63)
Proof.

\[
d\log(q(p^*(\xi, \zeta), \xi)) = \frac{1}{q(p^*(\xi, \zeta), \xi)} dq(p^*(\xi, \zeta), \xi)
\]
\[
= \frac{1}{q(p^*(\xi, \zeta), \xi)} \left( \frac{\partial q(p^*(\xi, \zeta), \xi) dp^*(\xi, \zeta)}{\partial p^*(\xi, \zeta)} + \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial \xi} d\xi \right) \tag{64}
\]
\[
d\log(p^*(\xi, \zeta)) = \frac{1}{p^*(\xi, \zeta)} dp^*(\xi, \zeta) \tag{65}
\]

Substituting equation 65 into 64 and applying the condition \(d\xi = 0\) completes the proof. \(\square\)

Proposition 2. If changes in price and demand are solely driven by shocks to the demand side, the following expression holds

\[
\frac{d\log(q^*)}{d\log(p^*)} = \frac{\varphi_q(p^*, \xi)}{\varphi_p(\xi, \zeta)} - \varepsilon(p^*, \xi) \tag{66}
\]

where \(\varphi_q(p^*, \xi) \equiv \frac{\partial q(p^*, \xi)}{\partial \xi} \frac{\xi}{q(p^*, \xi)}\) and \(\varphi_p(\xi, \zeta) \equiv \frac{\partial p(\xi, \zeta)}{\partial \xi} \frac{\xi}{p(\xi, \zeta)}\)

Proof.

\[
d\log(q(p^*(\xi, \zeta), \xi)) = \frac{1}{q(p^*(\xi, \zeta), \xi)} \left( \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial \xi} d\xi + \frac{\partial q(p^*(\xi, \zeta), \xi)}{\partial p^*(\xi, \zeta)} dp^*(\xi, \zeta) \right)
\]
\[
= (\varphi_q(p^*, \xi) - \varepsilon(p^*, \xi) \varphi_p(\xi, \zeta)) \frac{d\xi}{\xi} \tag{67}
\]
\[
d\log(p^*(\xi, \zeta)) = \frac{1}{p^*(\xi, \zeta)} dp^*(\xi, \zeta)
\]
\[
= \frac{1}{p^*(\xi, \zeta)} \left( \frac{\partial p^*(\xi, \zeta)}{\partial \xi} d\xi \right)
\]
\[
= \varphi_p(\xi, \zeta) \frac{d\xi}{\xi} \tag{68}
\]

\(\square\)
C Estimator

In this section, we derive the identification condition of our TPSFE estimator and discuss the endogenous selection problem that is present when estimating markup elasticities using a four dimensional (firm-product-destination-time) customs database. We begin by comparing the TPSFE estimator with a bunch of commonly used estimating procedures in the literature. Related analytical details are presented in the subsections C.1 – C.3.

Table 10 shows estimated markup elasticities of seven estimating procedures applied to the Chinese custom data. The first column shows estimates using the TPSFE estimator. The second column shows estimation results using destination demeaned variables but adding destination fixed effects rather than trade pattern fixed effects. The third and fourth columns show estimates applying the reghdfe estimator by Correia (2017), which automatically deals with the unbalanced panel problem in implementing multiple fixed effects. The last three columns perform a two-step procedure: S-period differenced variables are first calculated and then fixed effects are applied.

To appreciate the importance of the selection problem, note that all seven estimation procedures in table 10 would generate exactly the same estimates had the panel been totally balanced, i.e., if all firms exported all products to all destinations in all time periods. In practice, the customs data demonstrates a very high degree of unbalancedness. As a result, distinct estimators yield very different values of markup elasticities.

Comparing estimates from the first two columns of table 10, we can obtain a measure of the degree of market selection in estimating markup elasticities. If there is no market selection at the firm-product level, i.e., the set of destinations to which a firm-product pair exports is the same across all time periods, estimates of (1) and (2) will be exactly the same.

Market selection may or may not generate biases in markup estimates depending on whether the selection is endogenous. Although most firms do not export a product to the same set of markets across all time periods, the selection will not generate biased estimates unless the change in the markets is endogenous to changes in exchange rates and marginal cost. We find there is a subtle but important difference in applying firm-product-time + destination \((fpt,d)\) versus firm-product-destination + time \((fpd,t)\) fixed effects when the panel is unbalanced. In subsection C.2, we show the difference between these two estimates only exists if the selection is endogenous. We note that by taking the difference between these two estimates, a natural measure the degree of the endogenous selection bias can be obtained.\(^ {43}\) As shown in columns (3) and (4) of table 10, the markup elasticities estimated using \((ifd,t)\) fixed effects can be 40-50\% higher compared to those estimated using \((ift,d)\) effects, suggesting a non-negligible endogenous selection effect.

\(^{42}\)Note that destination-demean at firm-product-time level removes all factors that are invariant across destinations, e.g., the firm-product-time varying marginal cost.

\(^{43}\)The analytical difference in applying \((ifd,t)\) and \((ift,d)\) is given by expression (87).
While the empirical difference in applying these two partitions may be large or small depending on the market structure, the property of the goods and the underlying shocks (e.g., exchange rates versus tariff changes), we show that the correct data partition is firm-product-time + destination \((i ft, d)\) rather than the commonly perceived firm-product-destination + time \((ifd, t)\) if controlling unobserved marginal costs is the primary concern.\(^{44}\)

Two key elements matter in estimating markups by exploiting destination variation to control for marginal costs: (a) the correct data partition or fixed effects and (b) the correct way to implement the correct data partition.

Some estimation procedures implement a data partition that is not equivalent to the TPSFE estimator; these have the potential to include a large bias in estimated markup elasticities. In table 10 we find considerably higher estimates using the procedure that first takes \(S\)-period differences and then applied destination fixed effects. We discuss this point in more detail in subsections C.2 and C.3.

The rest of this section is organized as follows. Subsection C.1 derives the identification condition for the TPSFE estimator in a balanced panel. Subsection C.2 discusses bias due to endogenous selection of markets and compares the identification condition of our estimator with that of two commonly used alternatives. In subsection C.3, we simulate a set of numerical examples to illustrate the bias that may arise from an endogenously unbalanced panel and discuss various cases where the marginal cost is destination-specific. Subsection C.4 gives a structural interpretation of the required identification condition.

---

\(^{44}\)Examples in applying \((ifd, t)\) fixed effects in levels include Berman, Martin and Mayer (2012) and Chatterjee, Dix-Carneiro and Vichyanond (2013). However, note that main objectives of these two studies are not exactly the same as ours. Berman, Martin and Mayer (2012) already controlled for the estimated productivity in his specification. Therefore, the bias may be small even if a less favorable fixed effect is applied.
Table 10: Comparison across Estimators

<table>
<thead>
<tr>
<th>Destination Demean</th>
<th>S-period Difference</th>
<th>Fixed Effects</th>
<th>Stata Command</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>No</td>
<td>Trade Pattern</td>
<td>areg</td>
<td>23,750,519</td>
</tr>
<tr>
<td>No</td>
<td>No</td>
<td>Destination (d)</td>
<td>reghdfe</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>(ift, d)</td>
<td>reghdfe</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>(ifd, t)</td>
<td>reghdfe</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>Time (t)</td>
<td>reghdfe</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>S-Diff + (ifd, t)</td>
<td>reghdfe</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>S-Diff + (ift, d)</td>
<td>reghdfe</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>S-Diff + (ift, d)</td>
<td>reghdfe</td>
<td></td>
</tr>
</tbody>
</table>

2000 – 2014

<table>
<thead>
<tr>
<th>All Products</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.065***</td>
<td>0.022***</td>
<td>0.060***</td>
<td>0.090***</td>
<td>0.153***</td>
<td>0.127***</td>
<td>0.101***</td>
<td>23,750,519</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>High Differentiation</td>
<td>0.113***</td>
<td>0.015***</td>
<td>0.092***</td>
<td>0.144***</td>
<td>0.215***</td>
<td>0.228***</td>
<td>0.130***</td>
<td>10,251,672</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td></td>
</tr>
<tr>
<td>Low Differentiation</td>
<td>0.037***</td>
<td>0.026***</td>
<td>0.036***</td>
<td>0.052***</td>
<td>0.110***</td>
<td>0.056***</td>
<td>0.074***</td>
<td>13,498,847</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.006)</td>
<td>(0.004)</td>
<td></td>
</tr>
</tbody>
</table>

2006 – 2014

<table>
<thead>
<tr>
<th>All Products</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.073***</td>
<td>0.021***</td>
<td>0.080***</td>
<td>0.109***</td>
<td>0.166***</td>
<td>0.135***</td>
<td>0.110***</td>
<td>19,450,040</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>High Differentiation</td>
<td>0.120***</td>
<td>0.014***</td>
<td>0.112***</td>
<td>0.160***</td>
<td>0.233***</td>
<td>0.246***</td>
<td>0.148***</td>
<td>8,322,706</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.000)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.008)</td>
<td>(0.006)</td>
<td></td>
</tr>
<tr>
<td>Low Differentiation</td>
<td>0.049***</td>
<td>0.026***</td>
<td>0.056***</td>
<td>0.073***</td>
<td>0.118***</td>
<td>0.057***</td>
<td>0.081***</td>
<td>11,127,334</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.000)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.007)</td>
<td>(0.005)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Each cell reports the estimated markup elasticity to exchange rates from the estimation method specified on top of each column. Destination CPI, real GDP and M/GDP controls are included in all estimation methods; related estimates are omitted for conciseness. Each row indicates a different subsample. Within in a row, all methods are applied based on the same sample. The number of observations in the last column corresponds to Stage 7 of the data cleaning procedure specified in appendix D.4. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *. 
C.1 Balanced Panel

In a balanced panel, we can write the unbiasedness condition as

\[
\frac{1}{n_I n_F n_D n_T} \sum_i \sum_f \sum_d \sum_t (\tilde{m}_c_{ifdt} - \frac{1}{n_I n_F n_T} \sum_i \sum_f \sum_d \tilde{m}_c_{ifdt}) (\tilde{e}_{dt} - \frac{1}{n_T} \sum_t \tilde{e}_{dt}) = 0 \quad (69)
\]

Where \( n^j \) denotes the number of indices in dimension \( j \in \{i, f, d, t\} \); \( \bar{x}_j \) is defined as the mean of variable \( x \) taken over all dimensions other than \( j \); and

\[
\tilde{m}_c_{ifdt} - \frac{1}{n_I n_F n_T} \sum_i \sum_f \sum_d \tilde{m}_c_{ifdt} = m_{c_{ifdt}} - \frac{1}{n_D} \sum_d m_{c_{ifdt}}
\]

\[
= m_{c_{ifdt}} - m_{c_{if}} - (\overline{m}_c - \overline{c})
\]

\[
\tilde{e}_{dt} - \frac{1}{n_T} \sum_t \tilde{e}_{dt} = e_{dt} - \frac{1}{n_I n_F n_T} \sum_i \sum_f \sum_t e_{dt}
\]

\[
= e_{dt} - \bar{e}_t - (\bar{e}_d + \bar{e})
\]

Therefore, we can rewrite equation (69) as

\[
\frac{1}{n_I n_F n_D n_T} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_d - \overline{\psi}_{if} - \overline{\psi})(e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (70)
\]

Since exchange rates are not firm and product specific in a balanced panel, we can simplify equation (70) as:

\[
\frac{1}{n_D n_T} \sum_d \sum_t \left[ \frac{1}{n_I n_F} \sum_i \sum_f (\psi_{ifdt} - \overline{\psi}_d - \overline{\psi}_{if} + \overline{\psi}) \right] (e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (71)
\]

or write as

\[
\frac{1}{n_D n_T} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_t - \overline{\psi}_d + \overline{\psi})(e_{dt} - \bar{e}_t - \bar{e}_d + \bar{e}) = 0 \quad (72)
\]
Note that, as a deviation term, the compositional error must satisfy

\[ \frac{1}{n^D} D \sum_d \psi_{ifdt} = 0 \quad \forall ift \]  

(73)

With this relationship, we can write (72) as

\[ \frac{1}{n^D n^T} \sum_d \sum_t (\bar{\psi}_{dt} - \bar{\psi}_d)(e_{dt} - e_d) = 0 \]  

(74)

C.2 Unbalanced panel

In this subsection, we discuss a subtle, yet important difference in applying destination fixed effects to control for marginal costs in an endogenously unbalanced panel.

C.2.1 A parsimonious factor decomposition to illustrate the endogenous selection problem

To illustrate the problem raised by the endogenous selection of destination markets, we find it useful to decompose the markup and marginal cost components into collections of factors that vary along the four key dimensions \(i, f, d, t\). Omitting coefficients (i.e., \(\beta_i\), etc.) in front of the factors for conciseness, and accounting for all possible combinations among factors, we can write:

\[ \mu_{ifdt} = F_i + F_f + F_d + F_t + F_{if} + F_{id} + F_{it} + F_{fd} + F_{ft} + F_{dt} + F_{fdt} + F_{fdt} \]  

(75)

\[ \bar{mc}_{ift} = C_i + C_f + C_t + C_{if} + C_{it} + C_{ft} + C_{if} \]

Equation (75) captures all possible factors driving the markup and the (common-across-destinations) cost components. Demand factors include \(F_d\) and \(F_{id}\), which could be interpreted as destination-specific tastes for all goods and for good \(i\), respectively. Firm-level supply factors include \(C_f\) and \(C_{ft}\). Time-varying factors common to all firms (in our application, GDP growth and CPI inflation in the exporting country, etc.) are captured by \(F_t\). The bilateral nominal exchange rate between the origin and the destination country \(d\) is accounted for by the factor \(F_{dt}\), which also includes macro variables such as CPI and GDP growth in the destination country \(d\).
Panels of highly disaggregated firm-product-destination-time customs data are inherently unbalanced: frequently, the set of destinations served by a firm changes; arguably this occurs endogenously in response to exchange rate movements. Shifts in a firm’s trade pattern naturally correspond to the firm’s decision to discontinue sales in a market where the currency is too weak for its exports to be ‘competitive’ (vice versa for entry). This implies that observability of an ifdt price is likely to be correlated with movements of the bilateral exchange rate $F_{dt}$ and the unobserved marginal cost components.

To see the estimation problem raised by endogenous selection of markets, consider a standard practice in empirical studies of nominal exchange rate pass through. Usually, the first step in specifying ERPT models consists of taking a time difference. Time differencing is motivated by the fact that the series of nominal exchange rates or CPI indices cannot be directly compared across countries: the logged time difference, a growth rate, is instead comparable across destinations. When the objective of the estimation is to identify the export price markup elasticity, however, time differencing as an initial step is highly problematic. The selection of observations into the unbalanced, time-differenced panel depends on changes in bilateral exchange rates $F_{dt}$ and the unobserved marginal cost, $m_{c_{ift}}$. The change in the price in destination $d$ is only observed when the firm continues to sell the product in $d$ in both periods, $t$ and $t+s$. As already mentioned, this is less likely to occur when the producer’s currency has appreciated substantially relative to the local $d$ currency—the producer may be endogenously ‘priced out’ of the market in $d$. After time differencing, introducing firm-product fixed effects to control for marginal cost will be ineffective relative to the goal of identifying the parameter of interest because the two components, cost and the exchange rate, are not orthogonal in time differences.

For the case of S-period time differencing conditional on ifd, this implies:

$$\Delta s_{i|fd}P_{ifdt} = \Delta s_{i|fd}F_{it} + \Delta s_{i|fd}C_{it} + \Delta s_{i|fd}F_{dt} + \Delta s_{i|fd}C_{dt} + \Delta s_{i|fd}C_{ft} + \Delta s_{i|fd}C_{ift} + \Delta s_{i|fd}F_{ifdt} + \Delta s_{i|fd}F_{ifdt}$$

(76)

where $\Delta s_{ij}x_{j,t} \equiv x_{j,t} - x_{j,t-s}$ $\forall j \in \{f, i, f, d, fd, id, if, ifd\}$.

In other words, taking time differences changes the dimensions along which unobserved variables vary—making it impossible to control for them in later stages. By changing the panel dimension along which components of the firm-product marginal cost ($\Delta s_{i|fd}C_{it}, \Delta s_{i|fd}C_{ft}$) vary, taking the S-period difference within a firm-product-destination introduces the possibility

---

45 An advantage of using nominal exchange rates and CPI rather than the real exchange rate is that the nominal variables approach does not implicitly assume a relationship between nominal exchange rates and the relative CPI ratio.
of a bias due to a non-zero correlation between changes in cost components, and factors that are destination and time specific $\Delta_{\text{ifd}} F_{dt}$, e.g., destination-specific bilateral exchange rates. We provide a simulated example in C.3.1.

In comparison, the first stage of our TPSFE estimator yields:

$$\tilde{p}_{ifdt} = \tilde{F}_d + \tilde{F}_{id} + \tilde{F}_{fd} + \tilde{F}_{fdt} + \tilde{F}_{idt} + \tilde{F}_{ifdt} + \psi_{ifdt}$$

(77)

where $\tilde{x}_{ifdt} \equiv x_{ifdt} - \frac{1}{n} \sum_d x_{ifdt} \quad \forall x \in \{p_{ifdt}, \mu_{ifdt}, mc_{ifdt}, \psi_{ifdt}\}$. Clearly, the demeaning process differences out all the factors that are not destination-specific, including the firm-product time-varying marginal cost. If any destination-specific marginal cost components are present, destination demeaning will subtract out the average marginal cost across all destinations at the firm-product-time level and yield a term $\psi_{ifdt}$, reflecting any production cost differences across sets of varieties (e.g., compositional differences) sold in different destination markets under the same product code for the same firm in a particular time period.

C.2.2 The identification condition of our proposed estimator under an endogenously unbalanced panel

We now prove that our proposed estimator requires the same identification condition as the balanced panel case. For our proposed estimator, the identification condition can be written as

$$\frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t (\tilde{m}c_{ifdt,D_{ift}} - \frac{1}{n_{IFD}} \sum_i \sum_f \sum_d \tilde{m}c_{ifdt,D_{ift}})(\tilde{e}_{dt,D_{ift}} - \frac{1}{n_{IFD}} \sum_i \sum_f \sum_d \tilde{e}_{dt,D_{ift}}) = 0$$

(78)

where

$$\tilde{m}c_{ifdt,D_{ift}} \equiv mc_{ifdt} - \frac{1}{n_{ifD}} \sum_{d \in D_{ift}} mc_{ifdt}$$

$$\tilde{e}_{dt,D_{ift}} \equiv e_{dt} - \frac{1}{n_{ifD}} \sum_{d \in D_{ift}} e_{dt}$$

and $D_{ift}$ is the set of destinations to which a firm-product-time triplet exports and the number of destinations in this set is defined as $n_{ifD} \equiv |D_{ift}|$.

Since

$$\tilde{\psi}_{ifdt,D_{ift}} \equiv \psi_{ifdt} - \frac{1}{n_{ifD}} \sum_{d \in D_{ift}} \psi_{ifdt} = \psi_{ifdt} = \tilde{m}c_{ifdt,D_{ift}}$$
we can derive a condition similar to (70) as

$$\frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_d)(e_{dt} - \overline{e}_{t,Di_{ft}} - \overline{e}_d + \overline{e}) = 0 \quad (79)$$

Note that the destination average of the exchange rate is now firm, product and time specific, depending on the set of destinations $D_{i_{ft}}$, i.e.,

$$\begin{bmatrix} \overline{e}_{t,D_{i_{ft}}} \equiv \frac{1}{n_{D_{i_{ft}}}} \sum_{d \in D_{i_{ft}}} e_{dt} \end{bmatrix} \neq \begin{bmatrix} \overline{e}_t \equiv \frac{1}{n_{IFD}} \sum_i \sum_f \sum_d e_{dt} \end{bmatrix}$$

However, it can be shown that

$$\frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t (\psi_{ifdt} - \overline{\psi}_d)(\overline{e}_{t,D_{i_{ft}}} - \overline{e}_t) = 0 \quad (80)$$

To derive (80), it is useful to note that $\overline{e}_{t,D_{i_{ft}}}$ is not destination specific. This means (80) can be rewritten as

$$\frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t \left[ \sum_{d \in D_{i_{ft}}} (\psi_{ifdt} - \overline{\psi}_d) \right] (\overline{e}_{t,D_{i_{ft}}} - \overline{e}_t) \quad (81)$$

In addition, we know that, as a deviation term, $\psi_{ifdt}$ must satisfy

$$\sum_{d \in D_{i_{ft}}} \psi_{ifdt} = 0 \quad \forall i_{ft} \quad (82)$$

and that the following relationship holds

$$\frac{1}{n_{IFDT}} \sum_d \overline{\psi}_d \left[ \sum_i \sum_f \sum_t (\overline{e}_{t,D_{i_{ft}}} - \overline{e}_t) \right] = 0 \quad (83)$$

Using (83) and (82), it can be shown that expression (81) is always equal to zero.

Substituting (80) into (79) gives the required condition:

$$\frac{1}{n_{DT}} \sum_d \sum_t (\overline{\psi}_{dt} - \overline{\psi}_d)(e_{dt} - \overline{e}_d) = 0 \quad (84)$$

Therefore, in an unbalanced panel, our estimator requires the same condition as (74).
C.2.3 Alternative partitions require a more demanding condition to mitigate potential endogenous selection of markets

We derive the condition for unbiasedness for two alternative and closely-related partition methods that are commonly used in the exchange rate pass through literature. We show these methods can produce biased estimates due to endogenous selection of markets even in the case where the marginal cost component is not destination-specific. In general, the condition of alternative partitions can be simplified into two terms, the covariance between the compositional error and exchange rates as in equation (84) and an additional term capturing the endogenous selection of markets. We start with an alternative partition of firm-product-destination and time fixed effects ($ifd,t$). Let $T_{ifd}$ be the set of time periods a product-firm-destination triplet exports. The number of trading periods in this set is defined as $n_{ifd}^{T} \equiv |T_{ifd}|$. The unbiasedness condition can be decomposed into two terms using (4), i.e.,

$$
\frac{1}{n_{IFDT}^{T}} \sum_{i} \sum_{f} \sum_{d} \sum_{t} (\tilde{\psi}_{ifdt,T_{ifd}} - \frac{1}{n_{IFD}^{T}} \sum_{i} \sum_{f} \sum_{d} \tilde{\psi}_{ifdt,T_{ifd}})(\tilde{e}_{dt,T_{ifd}} - \frac{1}{n_{IFD}^{T}} \sum_{i} \sum_{f} \sum_{d} \tilde{e}_{dt,T_{ifd}}) + \\
\frac{1}{n_{IFDT}^{T}} \sum_{i} \sum_{f} \sum_{d} \sum_{t} (\tilde{mc}_{ift,T_{ifd}} - \frac{1}{n_{IFD}^{T}} \sum_{i} \sum_{f} \sum_{d} \tilde{mc}_{ift,T_{ifd}})(\tilde{e}_{dt,T_{ifd}} - \frac{1}{n_{IFD}^{T}} \sum_{i} \sum_{f} \sum_{d} \tilde{e}_{dt,T_{ifd}}) = 0
$$

where

$$
\tilde{\psi}_{ifdt,T_{ifd}} \equiv \psi_{ifdt} - \frac{1}{n_{ifd}^{T}} \sum_{d \in T_{ifd}} \psi_{ifdt} \\
\tilde{mc}_{ift,T_{ifd}} \equiv \tilde{mc}_{ift} - \frac{1}{n_{ifd}^{T}} \sum_{t \in T_{ifd}} \tilde{mc}_{ift} \\
\tilde{e}_{dt,T_{ifd}} \equiv \tilde{e}_{dt} - \frac{1}{n_{ifd}^{T}} \sum_{t \in T_{ifd}} \tilde{e}_{dt}
$$

Note that, even if the compositional term $\psi_{ifdt}$ is always zero, the second line of expression (85) may not necessarily be zero due to endogenous selection. The time demeaning operation at the firm-product-time level changes the dimensions along which the unobserved marginal cost $mc_{ift}$ varies, making $\tilde{mc}_{ift,T_{ifd}}$ a destination-specific object that moves along all four dimensions.
We now simplify equation (85) to get a clearer expression. Note that

\[
\frac{1}{n_t^T} \sum_i \sum_f \sum_d \tilde{MC}_{ift,T_{tf}} = \frac{1}{n_t^T} \sum_i \sum_f \sum_d \tilde{MC}_{ift} - \frac{1}{n_t^T} \sum_i \sum_f \sum_d \frac{1}{n_{ifd} \ t \in T_{ifd}} \sum \tilde{MC}_{ift} \\
= mc_t - mc \\
\frac{1}{n_t^T} \sum_i \sum_f \sum_d \tilde{e}_{dt,T_{ifd}} = \frac{1}{n_t^T} \sum_i \sum_f \sum_d e_{dt} - \frac{1}{n_t^T} \sum_i \sum_f \sum_d \frac{1}{n_{ifd} \ t \in T_{ifd}} \sum e_{dt} \\
= \bar{e}_t - \bar{e}
\]

Thus, the second line of expression (85) can be rewritten as

\[
\frac{1}{n^TDF} \sum_i \sum_f \sum_d \sum_t (mc_{ift} - mc_{ift,T_{ifd}} - mc_t + mc) (e_{dt} - \bar{e}_{d,T_{ifd}} - \bar{e}_t + \bar{e})
\]

(86)

Separating \( mc_{ift,T_{ifd}} \) and \( e_{d,T_{ifd}} \) from the above expression to simplify this condition gives

\[
\frac{1}{n^TDF} \sum_i \sum_f \sum_d \sum_t (mc_{ift} - mc_{ift,T_{ifd}} - mc_t + mc) (e_{dt} - \bar{e}_d - \bar{e}_t + \bar{e}) \\
+ \frac{1}{n^TDF} \sum_i \sum_f \sum_d \sum_t (mc_{ift} - mc_{ift,T_{ifd}}) (e_{dt} - \bar{e}_d - \bar{e}_t + \bar{e}) \\
+ \frac{1}{n^TDF} \sum_i \sum_f \sum_d \sum_t (mc_{ift} - mc_{ift,T_{ifd}}) (e_{dt} - \bar{e}_d - \bar{e}_t + \bar{e}) \\
+ \frac{1}{n^TDF} \sum_i \sum_f \sum_d \sum_t (mc_{ift} - mc_{ift,T_{ifd}}) (e_{dt} - \bar{e}_d - \bar{e}_t + \bar{e})
\]

where \( mc_{ift} \equiv \frac{1}{n_{ifd}^T} \sum_t \sum_d mc_{if,T_{ifd}} \) and \( \bar{e}_{d} \equiv \frac{1}{n_{ifd}^T} \sum_i \sum_f \sum_t e_{d,T_{ifd}} \). Note that the first three terms are zero. The last term (87) may or may not be zero depending on the nature of the unbalancedness.

\[
\frac{1}{n^TDF} \sum_i \sum_f \sum_d \sum_t (mc_{ift} - mc_{ift,T_{ifd}}) (\bar{e}_d - \bar{e}_{d,T_{ifd}})
\]

(87)

If the unbalanced panel arises from endogenous selection related to marginal cost shocks and exchange rate movements, expression (87) will in general not equal zero.
Therefore, the \((ifd,t)\) fixed effects require the following condition to hold:

\[
\frac{1}{n_{DT}} \sum_d \sum_t (\psi_{dt} - \bar{\psi}_d)(e_{dt} - \bar{e}_d) + \frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t (mc_{if} - mc_{if,t_{ifd}})(\bar{e}_d - e_{d,T_{ifd}}) = 0
\]

(88)

Similarly, the condition for taking time differences conditional on firm-product-destination triplets can be written as

\[
\frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \sum_t (\Delta_{s_{ifd}} \psi_{ifdt}) - \frac{1}{n_{IFD}} \sum_i \sum_f \sum_d \Delta_{s_{ifd}} \psi_{ifdt})(\Delta_{s_{ifd}} e_{dt}) - \frac{1}{n_{IFDT}} \sum_i \sum_f \sum_d \Delta_{s_{ifd}} e_{dt} = 0
\]

(89)

where

\[
\Delta_{s_{ifd}} \psi_{ifdt} \equiv \psi_{ifdt} - \psi_{ifd,t-s_{ifd}} \\
\Delta_{s_{ifd}} mc_{ift} \equiv mc_{ift} - mc_{if,t-s_{ifd}} \\
\Delta_{s_{ifd}} e_{dt} \equiv e_{dt} - e_{d,t-s_{ifd}}
\]

Even if marginal cost is not destination-specific and the first line is always zero, estimates can still be biased as the second line of (89) can be very different from zero due to endogenous selection of markets. We find further decomposing (89) does not provide more intuition. We turn to illustrating the properties of our estimator and comparing it to alternative methods with simulated examples.

C.3 Simulated Examples on Endogenous Market Selection and Destination Specific Marginal Costs

C.3.1 Simulated example: the bias from endogenously unbalanced panels

We now suppress the product dimension and construct a three dimensional numerical example in which the price \(p_{fdt}\) is determined by three components, the markup adjustment in response to bilateral exchange rates, \(\beta_1 e_{dt}\), the unobserved marginal cost, \(\beta_2 mc_{ft}\), and a residual term, \(u_{fdt}\).
The data generating process is given as follows:

\[
p_{fdt} = \beta_1 e_{dt} + \beta_2 mc_{ft} + u_{fdt} \tag{90}
\]

\[
e_{dt} = \mathcal{F}_d + \mathcal{C}_t + \mathcal{F}_d \ast \mathcal{F}_t
\]

\[
c_{ft} = \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f \ast \mathcal{C}_t
\]

In this example, bilateral exchange rates, \( e_{dt} \), co-move with firm specific marginal costs, \( mc_{ft} \), through the co-movement between factors \( \mathcal{F}_t \) and \( \mathcal{C}_t \). The formulation of factors and the residual term is given by (91).

\[
u_{fdt} = \mathcal{I}_1 C_f + \mathcal{I}_2 F_d + \mathcal{I}_3 F_t + \epsilon_{fdt}
\]

\[
\mathcal{F}_d \sim N(0, 1) \quad \mathcal{C}_f \sim N(0, 1) \quad \mathcal{F}_t \sim N(0, 1) \quad \epsilon_{fdt} \sim N(0, 1)
\tag{91}
\]

where \( \mathcal{I} \) is an indicator variable that takes values of 0 or 1. For instance, \( \mathcal{I}_2 \) reflects the cross-destination compatibility problem, i.e., cross-destination comparisons of macro variables such as nominal exchange rates and CPI are meaningless. In each simulation, a balanced panel with 200 firms, 10 destinations and 10 time periods is generated, i.e., \( n^F = 200, n^D = 10, n^T = 10 \).

For the unbalanced panel experiment, we create missing observations conditional on realised exchange rate and marginal cost shocks in the generated balanced panel, i.e,

\[
p_{fdt} = \begin{cases} 
\text{missing} & \text{if top 20 percentile of exchange rate shocks } (e_{dt} - e_{dt-1}) \text{ at time } t \\
\text{observed} & \text{otherwise}
\end{cases}
\]

Our selection rule filters out trade flows from exporters that receive a high positive exchange rate shock and a high positive marginal cost shock at time \( t \). Both shocks induce the price to rise, resulting in lower demand. As a result, the exporter may no longer find it optimal to trade.\(^{46}\)

Table 11 presents our estimation results. The first column indicates the sources of variation that are active in the data generating process of \( u_{fdt} \). In the first row, by setting all indicator variables to zero, the price is determined by the shocks that drive the exchange rate and marginal cost. In the second row, potential single dimensional distortions could directly impact the price. Both rows \( (0 0 0) \) and \( (1 1 1) \) show that for a balanced panel, all three estimators return the

\(^{46}\)We also allow for other patterns of random drops to make sure the environment we constructed is similar to what we observe in the customs database. In particular, for each firm-year combination, we randomly generate 3 missing values (out of 10) along the destination dimension. We repeat this process for firm-destination combinations, and generating 3 missing values among the remaining observations. The advantage of using two separate processes compared to a random drop at the firm level lies in that the former allows the structure of missing values to differ along the time and destination dimensions.
correct estimate of the true parameter (listed in the last column).

However, in an unbalanced panel, only the TPSFE procedure is capable of producing the correct estimate. S-period differences with time fixed effects (i.e., the Time Diff column) shows a significant upward bias while \((f_{d,t})\) fixed effects generate a significant downward bias. Our simulation suggests that one needs to be careful in applying multiple fixed effects in an unbalanced panel with endogenous chosen trade patterns.

Table 11: Performance of Estimators: Balanced v.s. Unbalanced Panel

<table>
<thead>
<tr>
<th></th>
<th>Balanced Panel</th>
<th>Unbalanced Panel</th>
<th>Theoretical</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(I_1) (I_2) (I_3)</td>
<td>Time Diff (f_{d,t}) TPSFE</td>
<td>Time Diff (f_{d,t}) TPSFE</td>
</tr>
<tr>
<td>0 0 0</td>
<td>1.00*** (0.01) 1.00*** (0.01)</td>
<td>1.00*** (0.01) 1.00*** (0.01)</td>
<td>1.00*** (0.02) 0.85*** (0.02) 1.00*** (0.02)</td>
</tr>
<tr>
<td>1 1 1</td>
<td>1.00*** (0.02) 1.00*** (0.02)</td>
<td>1.00*** (0.02) 1.00*** (0.02)</td>
<td>1.00*** (0.02) 0.84*** (0.02) 1.00*** (0.02)</td>
</tr>
</tbody>
</table>

Estimates and standard errors are calculated from the average of 100 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘Time Diff’ column presents estimates using S-period time differenced variables at the firm-destination level adding time fixed effects. The ‘\(f_{d,t}\)’ column presents estimates applying firm-product and time fixed effects in the reghdfe estimator. The ‘TPSFE’ column presents estimates applying our trade pattern sequential fixed effects estimator.

We provide a simple analytical decomposition to show why the difference arises. We first evaluate the “Time Diff” approach where the S-period time difference is taken.

\[
\Delta_{s_{i,f,d}} p_{f,d} = \beta_1 \Delta_{s_{i,f,d}} e_{d,t} + \beta_2 \Delta_{s_{i,f,d}} mc_{f,t} + \Delta_{s_{i,f,d}} u_{f,d} \tag{92}
\]

where

\[
\Delta_{s_{i,f,d}} e_{d,t} = F_t - F_{t-s_{i,f,d}} + F_d(F_t - F_{t-s_{i,f,d}})
\]

\[
\Delta_{s_{i,f,d}} mc_{f,t} = C_t - C_{t-s_{i,f,d}} + C_f(C_t - C_{t-s_{i,f,d}})
\]

It can be seen clearly that \(\Delta_{s_{i,f,d}} mc_{f,t}\) is now varying over all three dimensions \((f_{d,t})\), making the unobserved marginal cost term uncontrollable. Adding additional fixed effect dummies in the later stage will not help to control for the unobserved marginal cost.

Our method deals with the unobserved marginal cost in the first stage. As illustrated in equation (93), the unobserved marginal cost term is controlled by the destination demeaning
process.

\[ \tilde{P}_{f,t,D} = \beta_1 \tilde{e}_{t,D} + \bar{u}_{f,t} \]  
\[ \tilde{e}_{t,D} = e_{t,D} - \sum_{d \in D} \frac{e_{d,t}}{n_{f,t}^D} = \tilde{F}_{t,D} (1 + F_d) \]  

C.3.2 Simulated examples: various cases of destination-specific cost components

In what follows, we expand our numerical example in C.3.1 and discuss how compositional error would affect our estimates under various scenarios. Specifically, we add \( \psi_{f,t,D} \), the deviation from the mean marginal cost, to the pricing equation.

In this exercise, it is important to note that condition (73) provides additional information which helps to pin down the functional form of the compositional term. In general, we could have set \( \psi_{f,t,D} = A_d + B_{f,t} + A_d * B_{f,t} \). However, as a deviation term, the compositional error must satisfy (73) suggesting a multiplicative relationship between factors varying at the destination dimension, \( A_d \), and factors varying at other dimensions, \( B_{f,t} \), i.e.,

\[ \psi_{f,t,D} = A_d * B_{f,t} \]  

with the restriction that \( \frac{1}{n_{f,t}^D} \sum_{d \in D} A_d = 0 \forall f,t \). In what follows, we will consider various formulations of \( A_d \) and \( B_{f,t} \), and compare the performance of estimators.

We start with the case where components within the compositional term, \( A_d \) and \( B_{f,t} \), are random and uncorrelated with factors in \( e_{d,t} \) and \( m_{c,f,t} \), i.e.,

\[ p_{f,t} = \beta_1 e_{t,D} + \beta_2 m_{c,f,t} + \psi_{f,t,D} + u_{f,t} \]  
\[ e_{t,D} = F_d + F_t + F_d * F_t \]  
\[ m_{c,f,t} = C_f + C_t + C_f * C_t \]  
\[ \psi_{f,t,D} = A_d * B_{f,t} \]  
\[ A_d \sim N(0,1) \quad B_{f,t} \sim N(\mu, \sigma) \]

Parameters are set to 1 in the simulation for simplicity, i.e., \( \beta_1 = \beta_2 = 1 \).
Table 12: Performance of Estimators in the Presence of Random Compositional Errors

<table>
<thead>
<tr>
<th></th>
<th>Balanced Panel</th>
<th>Unbalanced Panel</th>
<th>Theoretical</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time Diff</td>
<td>( fd_t )</td>
<td>TPSFE</td>
</tr>
<tr>
<td>( I_1 I_2 I_3 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \mu = 0 )</td>
<td>1.00***</td>
<td>1.00***</td>
<td>1.00***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>( \mu = 0.1 )</td>
<td>1.00***</td>
<td>1.00***</td>
<td>1.00***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘Time Diff’ column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The ‘\( fd_t \)’ column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The ‘TPSFE’ column represents estimates applying our trade pattern sequential fixed effects estimator.

Table 12 presents our simulation results. Since the compositional error is random, it will not bias the estimate. In a balanced panel, all three estimators give the correct estimate of 1 with a slight increase in standard errors relative to the values in Table 11 due to the compositional error. In the unbalanced panel, all three estimators give estimates comparable to Table 11, again with a slight increase in standard errors.

Next, we keep \( A_d \) random and uncorrelated with \( F_d \) but set \( B_{ft} = \mu + mc_{ft} \). This setup allows a dependence between the compositional term and firm level factors. For example, the magnitude of the compositional error may depend on the productivity of the firm.

\[
p_{fdt} = \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt}
\]
\[
e_{dt} = F_d + F_t + F_d * F_t
\]
\[
mc_{ft} = C_f + C_t + C_f * C_t
\]
\[
\psi_{fdt} = A_d * (\mu + mc_{ft})
\]
\[
A_d \sim N(0, 1)
\]

Table 13 shows that the firm-level dependence of the compositional error will not generate a bias as long as the destination dimension components of the bilateral exchange rates are uncorrelated with the destination dimension components of the composition error, \( A_d \).
Table 13: Performance of Estimators: Firm-level Dependence of the Compositional Error

<table>
<thead>
<tr>
<th>$I_1$</th>
<th>$I_2$</th>
<th>$I_3$</th>
<th>Balanced Panel</th>
<th>Unbalanced Panel</th>
<th>Theoretical</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Time Diff</td>
<td>$f_d, t$</td>
<td>TPSFE</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\mu = 0$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 0 0</td>
<td></td>
<td></td>
<td>0.96***</td>
<td>0.96***</td>
<td>0.96***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>1 1 1</td>
<td></td>
<td></td>
<td>1.02***</td>
<td>1.02***</td>
<td>1.02***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\mu = 0.1$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 0 0</td>
<td></td>
<td></td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>1 1 1</td>
<td></td>
<td></td>
<td>0.99***</td>
<td>0.99***</td>
<td>0.99***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘Time Diff’ column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The ‘$f_d, t$’ column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The ‘TPSFE’ column represents estimates applying our trade pattern sequential fixed effects estimator.

In the next example, for each firm-product-time pair, the compositional error is positively correlated with the bilateral exchange rates at the destination dimension. Simulation results are shown in table 14. Our estimator is still unbiased.

\[
p_{f_d t} = \beta_1 e_{d t} + \beta_2 m_c f_t + \psi_{f_d t} + u_{f_d t}
\]

\[
e_{d t} = F_d + F_t + F_d * F_t
\]

\[
m_c f_t = C_f + C_t + C_f * C_t
\]

\[
\psi_{f_d t} = F_d * B_{f t}
\]

\[
F_d \sim N(0, 1) \quad B_{f t} \sim N(\mu, \sigma)
\]
Table 14: Performance of Estimators: Destination Dependence of the Compositional Error

<table>
<thead>
<tr>
<th>$I_1$</th>
<th>$I_2$</th>
<th>$I_3$</th>
<th>Balanced Panel</th>
<th>Unbalanced Panel</th>
<th>Theoretical</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Time Diff</td>
<td>$fd,t$</td>
<td>TPSFE</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>$\mu = 0$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1.00***</td>
<td>1.00***</td>
<td>1.00***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1.00***</td>
<td>1.00***</td>
<td>1.00***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>$\mu = 0.1$</td>
<td></td>
<td></td>
<td>1.00***</td>
<td>1.00***</td>
<td>1.00***</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>0</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1.00***</td>
<td>1.00***</td>
<td>1.00***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘Time Diff’ column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The ‘$fd,t$’ column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The ‘TPSFE’ column represents estimates applying our trade pattern sequential fixed effects estimator.

Among all simulations, the only problematic one is the following setup where the destination component of the compositional error is correlated with the destination component of bilateral exchange rates and the firm-time dimension component of the compositional error is correlated with unobserved firm-time factors.

In this case, the bias of the compositional error depends on two parameters, the parameter $\mu_3$ controlling the conditional covariance at the destination dimension $cov_{d|ft}(\psi_{fdt}, e_{dt})$, and the parameter $\mu_2$ controlling conditional covariance at the firm-time dimension $cov_{ft|d}(\psi_{fdt}, mc_{ft})$.

\[
\begin{align*}
  p_{fdt} &= \beta_1 e_{dt} + \beta_2 mc_{ft} + \psi_{fdt} + u_{fdt} \\
  e_{dt} &= \mathcal{F}_d + \mathcal{F}_t + \mathcal{F}_d \ast \mathcal{F}_t \\
  mc_{ft} &= \mathcal{C}_f + \mathcal{C}_t + \mathcal{C}_f \ast \mathcal{C}_t \\
  \psi_{fdt} &= \mu_3 \mathcal{F}_d \ast (\mu_1 + \mu_2 mc_{ft}) \\
  \mathcal{F}_d &\sim N(0, 1)
\end{align*}
\]
Table 15: Performance of Estimators: Destination and Firm-time Compositional Errors

<table>
<thead>
<tr>
<th></th>
<th>Balanced Panel</th>
<th>Unbalanced Panel</th>
<th>Theoretical</th>
</tr>
</thead>
<tbody>
<tr>
<td>µ₁  µ₂  µ₃</td>
<td>Time Diff</td>
<td>fd,t</td>
<td>TPSFE</td>
</tr>
<tr>
<td>0 1 1</td>
<td>2.00***</td>
<td>2.00***</td>
<td>2.00***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>0.1 1 1</td>
<td>1.99***</td>
<td>1.99***</td>
<td>1.99***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>0.1 0.1 1</td>
<td>1.10***</td>
<td>1.10***</td>
<td>1.10***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>0.1 1 0.1</td>
<td>1.10***</td>
<td>1.10***</td>
<td>1.10***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>0.1 0.1 0.1</td>
<td>1.01***</td>
<td>1.01***</td>
<td>1.01***</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

Estimates and standard errors are calculated from the average of 200 simulations. Each simulation contains a randomly generated sample of 200 firms, 10 destinations and 10 time periods based on the data generating process specified in the paper. The ‘Time Diff’ column represents estimates using S-period differenced variables at the firm-destination level adding time fixed effects. The ‘fd,t’ column represents estimates applying firm-product and time fixed effects using the reghdfe estimator. The ‘TPSFE’ column represents estimates applying our trade pattern sequential fixed effects estimator.

Table 15 presents results on five parametrizations. The first row gives the results in the setup where both destination and firm-product covariances are high, i.e., \( \text{cov}_{d|ft}(\psi_{fdt}, e_{dt}) = 1 \) and \( \text{cov}_{ft|d}(\psi_{fdt}, mc_{ft}) = 1 \). In this setting, all three estimators generate upward biased estimates compared to the true markup elasticity \( \beta_1 = 1 \).⁴⁷ Results in the second row show changing values of the mean of the component varying along the firm time dimension, \( \mu_1 \), will not affect the estimate. As this relationship is generally true in all specifications, we will focus on exploiting variations in \( \mu_2 \) and \( \mu_3 \) in rows 3-5. Row 3 presents the case where the destination dimension covariance is low but the firm-time dimension covariance is high. Row 4 is the reverse of 3. Row 5 presents the case where both covariances are low, \( \text{cov}_{d|ft}(\psi_{fdt}, e_{dt}) = 0.1 \) and \( \text{cov}_{ft|d}(\psi_{fdt}, mc_{ft}) = 0.1 \). Through the last three rows of table 15, we document that the compositional term is a second order problem, i.e., the bias will be small if either of these two covariances are small.

We surmise that a large proportion of destination variation in nominal bilateral exchange rates is driven by nominal differences that can be considered as randomly distributed. This nominal noise in exchange rates would dilute the covariance term, resulting in a small \( \text{cov}_{d|ft}(\psi_{fdt}, e_{dt}) \). Therefore, with a sufficiently small destination dimension covariance, \( \text{cov}_{d|ft}(\psi_{fdt}, e_{dt}) \), and a reasonable firm-time level covariance, \( \text{cov}_{ft|d}(\psi_{fdt}, mc_{ft}) \), the degree of compositional bias should be small.

⁴⁷The theoretical number in the table is calculated based on the statistical relationship imposed by a particular setup. In the case of Table 15, the theoretical number is calculated as \( \beta_1 + \mu_3 \cdot \mu_2 \).
C.4 A Structural Interpretation of Assumptions Required by Our Estimator

In this subsection, we extend the framework of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) to add the destination dimension and discuss the structural assumptions that would be required for our main identification condition (5) to be satisfied.

C.4.1 Assumptions

In this extension, we incorporate destination-specific inputs \( \{V_{fidt}, K_{fidt}\} \) and productivity differences, \( \Psi_{fid} \) at the firm and product level. In addition, we allow for the production function and Hicks-neutral productivity to be firm-product specific.

\[ Q_{fidt} = F_{fi}(V_{fidt}, K_{fidt}) \Omega_{fit} \Psi_{fid} \]  

where \( Q_{fidt} \) represents the quantity of exports for product \( i \) from firm \( f \) to destinations \( d \) at time \( t \); \( V_{fidt} \) denotes a vector of variable inputs, \( \{V_{1}^{1}, V_{2}^{1}, ... , V_{v}^{1}\} \); \( K_{fit} \) denotes a vector of dynamic inputs; a firm-product pair make decisions on allocating its dynamic inputs across destinations \( D_{fit} \) in each time period, \( \{K_{1}^{1}, K_{2}^{1}, ... , K_{k}^{1}\} \).

1. The production technology is firm-product-specific.

2. \( F_{fi}(.) \) is continuous and twice differentiable w.r.t. at least one element of \( V_{fidt} \), and this element of \( V_{fidt} \) is a static (i.e., freely adjustable or variable) input in the production of product \( i \).

3. \( F_{fi}(.) \) is constant return to scale.

4. Hicks-neutral productivity \( \Omega_{fit} \) is log-additive.

5. The destination specific technology advantage \( \Psi_{fid} \) takes a log-additive form and is not time varying.

6. Input prices \( W_{fit} \) are firm-product-time specific.

7. The state variables of the firm are

\[ s_{fit} = \{D_{fit}, K_{fit}, \Omega_{fit}, \Psi_{fid}, G_{fi}, r_{fidt}\} \]  

where \( G_{fi} \) includes variables indicating firm and product properties, e.g., firm registration types, product differentiation indicators. \( r_{fidt} \) collects other observables including variables
that track the destination market conditions, such as the bilateral exchange rate and destination CPI.

8. Firms minimize short-run costs taking output quantity and input prices $W_{fit}$ at time $t$ as given.

Note that the assumptions 1, 2, 4, 8 are standard in the literature. We inherit them from De Loecker, Goldberg, Khandelwal and Pavcnik (2016) but allow the production function to be firm specific and the Hicks-neutral productivity to depend on the product. Assumption 5 is a relaxation rather than a restriction compared to the existing literature as it allows the additive productivity to be destination-specific.

Assumptions 6 and 7 indicate that prices of inputs are at the firm and product level. These two conditions indicate that firms source inputs at the product level and then allocate these inputs into production for different destinations. Note that the firm can arrange different quantities of inputs and have different marginal costs across destinations for the same product.

The assumption that is crucial to our identification is 3. This condition implies the marginal cost at the firm-product-destination level does not depend on the quantity produced. If changes in relative demand across destinations, which will lead to quantity differences as long as the price is not fully sticky in the destination market, is also associated changes in relative marginal costs, condition 5 will be violated. As described in the next subsection, at the solution of the cost minimization problem, this condition ensures that the difference in the marginal costs across destinations is proportional to technology differences $\frac{\Psi_{fid}}{\Psi_{fid}}$.

C.4.2 The cost minimization problem by firm-product pair

$$L(V_{fidt}, K_{fidt}, \lambda_{fidt}) = \sum_{v=1}^{V} W_{fit}^v \sum_{d \in D_{fit}} V_{fidt}^v + \sum_{k=1}^{K} R_{fit}^k \left( \sum_{d \in D_{fit}} K_{fidt}^k - K_{fit}^k \right) + \sum_{d \in D_{fit}} \lambda_{fidt}[Q_{fidt} - F_{fi}(V_{fidt}, K_{fidt})\Omega_{fit}\Psi_{fid}]$$

Where $K_{fit}^k$ is the accumulated capital input $k$ in the previous period; $K_{fidt}^k$ stands for the corresponding allocation for destination $d$; $R_{fit}^k$ is the implied cost of capital.\(^{48}\)

F.O.C.

$$\frac{\partial L_{fit}}{\partial V_{fit}^v} = W_{fit}^v - \lambda_{fidt} \Omega_{fit} \Psi_{fid} \frac{\partial F_{fi}(\cdot)}{\partial V_{fidt}^v} = 0$$  \((97)\)

\(^{48}\)The assumption that the production function $F_{fi}(\cdot)$ is firm-product-specific ensures the implied cost of capital $R_{fit}^k$ being not destination-specific.
\[
\frac{\partial L_{fit}}{\partial K_{fit}} = R_{fit}^k - \lambda_{fit} \Omega_{fit} \Psi_{fit} \frac{\partial F_{fi}(\cdot)}{\partial K_{fit}} = 0 \quad (98)
\]

Conditions (97) and (98) need to hold across inputs and across destinations, which implies

\[
W^1_{fit} = \frac{\partial F_{fi}(\cdot)}{\partial V^1_{fit}} = \frac{\partial F_{fi}(\cdot)}{\partial V^1_{fit}} = \ldots = \frac{\partial F_{fi}(\cdot)}{\partial V^1_{fit}} \quad \forall v = 1, \ldots, V \quad (99)
\]

\[
W^v_{fit} = \frac{\partial F_{fi}(\cdot)}{\partial V^v_{fit}} = \frac{\partial F_{fi}(\cdot)}{\partial V^v_{fit}} = \ldots = \frac{\partial F_{fi}(\cdot)}{\partial V^v_{fit}} \quad \forall v, k \quad (100)
\]

Note that the production function is assumed to be firm-product specific and constant return to scale. Together with equations (99) and (100), these assumptions imply the allocation of variable inputs is proportional to the ratio of the productivity deflated outputs across destinations. That is,

\[
\frac{Q_{fit}}{\Omega_{fit} \Psi_{fit}} = c \cdot \frac{Q_{fit}}{\Omega_{fit} \Psi_{fit}'} \rightarrow cV^*_fi = V^*_f, t \quad and \quad cK^*_fi = K^*_f, t \quad (101)
\]

Utilizing the relationship of (101) and the assumption that \( F_{fi}(\cdot) \) is constant return to scale, we can show

\[
c_{fit} \frac{\partial F_{fi}(V^*_{fit}, K^*_{fit})}{\partial V^v_{fit}} = \frac{\partial [c_{fit} F_{fi}(V^*_{fit}, K^*_{fit})]}{\partial V^v_{fit}} = \frac{\partial F_{fi}(c_{fit} V^*_{fit}, c_{fit} K^*_{fit})}{\partial V^v_{fit}} = \frac{\partial F_{fi}(V^*_{fit}, K^*_{fit})}{\partial V^v_{fit}} \quad (102)
\]

where \( c_{fit} \equiv \frac{Q_{fit}}{\Omega_{fit} \Psi_{fit}'} \). Rearrange (99) and get

\[
\lambda_{fit} = \left( \frac{\Omega_{fit} \Psi_{fit} \partial F_{fi}(V^*_{fit}, K^*_{fit})}{W^v_{fit} \partial V^v_{fit}} \right)^{-1} \quad (103)
\]

Under this setup, the relative marginal cost across destinations is static depending on the relative productivity difference across destinations, i.e.,

\[
\frac{\lambda_{fit}/Q_{fit}}{\lambda_{fit}/Q_{fit}'} = \frac{\Psi_{fit}'}{\Psi_{fit}} \quad (104)
\]

Although the marginal cost is firm-product-destination specific and time varying, the relative marginal cost is not. Therefore, condition (5) is satisfied.
C.4.3 An alternative extension

An alternative and more direct extension of De Loecker, Goldberg, Khandelwal and Pavcnik (2016) is to simply redefine the product variety in their model. Notably, if we redefine product + destination as a variety, i.e., \( j = \{i, d\} \), then the original setting and assumptions will go through.

We argue that this extension is less favorable for two reasons. The first one is practical. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) define a product variety as a two-digit industry. The need to define a product at industry level is mainly due to data restrictions. Had they used a more refined product definition, their estimator would suffer from a small sample problem and they would not have enough power to estimate. The small sample problem will be much more serve if one defines product + destination as a variety. This is not only due to the smaller number of observations by splitting the estimation sample into a smaller cell but also because of the frequent changes in the set of destinations a firm-product pair exports to.

The second one is related to the correct conceptual assumptions regarding production functions. De Loecker, Goldberg, Khandelwal and Pavcnik (2016) relies on the assumption that the functional form of the production function is the same for single- and multi-product firms. In the context of this extension, the identification condition would require the functional form of the production function to be product-destination specific and invariant along the firm dimension. In the context of our problem in which controlling for firm-product level marginal cost is the primary concern, we think that keeping the flexibility of the production function at the product level is extremely valuable.
D Data

D.1 Descriptive Statistics of Chinese Customs Data

China’s dramatic increase in export value over 2000-2014 includes extensive margin net entry on both the firm and firm-product dimensions. See Table 16.

Table 16: Chinese exports: firms, products and values, 2000-2014

<table>
<thead>
<tr>
<th>Year</th>
<th>Products</th>
<th>Exporters</th>
<th>Product-Exporter Pairs</th>
<th>Obs.</th>
<th>Value (billions US$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>6,712</td>
<td>62,746</td>
<td>904,111</td>
<td>1,953,638</td>
<td>249</td>
</tr>
<tr>
<td>2001</td>
<td>6,722</td>
<td>68,487</td>
<td>991,015</td>
<td>2,197,705</td>
<td>291</td>
</tr>
<tr>
<td>2002</td>
<td>6,892</td>
<td>78,607</td>
<td>1,195,324</td>
<td>2,672,837</td>
<td>325</td>
</tr>
<tr>
<td>2003</td>
<td>7,013</td>
<td>95,683</td>
<td>1,475,588</td>
<td>3,328,320</td>
<td>438</td>
</tr>
<tr>
<td>2004</td>
<td>7,017</td>
<td>120,567</td>
<td>1,826,966</td>
<td>4,125,819</td>
<td>593</td>
</tr>
<tr>
<td>2005</td>
<td>7,125</td>
<td>142,413</td>
<td>2,277,801</td>
<td>5,252,820</td>
<td>753</td>
</tr>
<tr>
<td>2006</td>
<td>7,171</td>
<td>171,169</td>
<td>2,907,975</td>
<td>6,312,897</td>
<td>967</td>
</tr>
<tr>
<td>2007</td>
<td>7,172</td>
<td>193,567</td>
<td>3,296,238</td>
<td>7,519,615</td>
<td>1,220</td>
</tr>
<tr>
<td>2008</td>
<td>7,213</td>
<td>206,529</td>
<td>3,244,484</td>
<td>7,995,266</td>
<td>1,431</td>
</tr>
<tr>
<td>2009</td>
<td>7,322</td>
<td>216,219</td>
<td>3,363,610</td>
<td>8,263,509</td>
<td>1,202</td>
</tr>
<tr>
<td>2010</td>
<td>7,363</td>
<td>234,366</td>
<td>3,847,708</td>
<td>9,913,754</td>
<td>1,577</td>
</tr>
<tr>
<td>2011</td>
<td>7,404</td>
<td>254,617</td>
<td>4,153,534</td>
<td>10,645,699</td>
<td>1,898</td>
</tr>
<tr>
<td>2012</td>
<td>7,564</td>
<td>266,842</td>
<td>4,171,770</td>
<td>11,057,899</td>
<td>2,016</td>
</tr>
<tr>
<td>2013</td>
<td>7,579</td>
<td>279,428</td>
<td>4,140,897</td>
<td>11,643,683</td>
<td>2,176</td>
</tr>
<tr>
<td>2014</td>
<td>7,641</td>
<td>295,309</td>
<td>4,555,912</td>
<td>12,297,195</td>
<td>2,310</td>
</tr>
</tbody>
</table>

D.2 The “Happy Few:” Multi-product, multi-destination exporters

The key to identifying price responses to exchange rate movements for our estimator relies on cross-destination market variation in prices. Following Mayer, Melitz and Ottaviano (2014), we use the 2007 cross section of the Chinese Customs Database to document in table 17 that a “happy few” exporters are responsible for most of China’s exports. The top panel provides a breakdown of the number of export transactions by the count of products and destinations served by a firm exporting from China. The bottom panel presents the respective shares of export value by firms that differ
Table 17: Multi-product, multi-destination exporters (2007)

<table>
<thead>
<tr>
<th>No. of Products</th>
<th>Number of Countries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>by Share of Exporters</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>13.5</td>
</tr>
<tr>
<td>2-5</td>
<td>9.5</td>
</tr>
<tr>
<td>6-10</td>
<td>2.2</td>
</tr>
<tr>
<td>10+</td>
<td>2.1</td>
</tr>
<tr>
<td>Total</td>
<td>27.2</td>
</tr>
</tbody>
</table>

| by Share of Exports |     |     |      |     |       |
| 1                 | 1.2 | 1.3 | 0.8  | 1.3 | 4.7   |
| 2-5               | 1.9 | 4.3 | 3.3  | 8.8 | 18.4  |
| 6-10              | 0.6 | 2.2 | 2.0  | 8.1 | 13.0  |
| 10+               | 1.6 | 4.0 | 4.2  | 54.0| 63.9  |
| Total             | 5.4 | 11.9| 10.4 | 72.3| 100.0 |

Note: Each cell in the top panel is the percentage of observations in the Chinese customs data in 2007 that fall under the relevant description. The bottom panel presents the corresponding value of exports.

by exported product count and foreign markets reached. Overall, we see that multi-destination exporters represent almost three-quarters of export transactions (row 5 of the top panel of table 17, 33.1+14.7+25.0) and are responsible for 94.6% of export value (row 5 of the bottom panel of table 17). These statistics highlight two important facts: (1) the identification scheme based on multi-destination exporters uses observations from those firms that are most important to China’s trade and (2) the vast majority of firms are not single-product exporters. The shares of export transactions and export value by count of products and destination markets are relatively stable across years in our sample period. Tables for other years are available in an on-line appendix.

Conversely, we see that transactions by single-destination firms account for a small share of total Chinese export value. In the top left cell of the top panel of table 17, we observe that 13.5% of observations on exports in the Chinese Customs Database were articles exported to a single destination by a single product firm. However, these transactions comprised only 1.2% of Chinese export value in 2007. The bottom row of the top panel shows that slightly more than one quarter of export transactions in 2007 were products exported by a firm to a single destination. However, the last row of the bottom panel indicates that the value of these transactions by single-destination exporters was only 5.4% of total Chinese exports.
D.3 In which currency do exporters from China invoice?

The Chinese Customs Authority reports the value of export shipments in US dollars, but does not provide any information about whether the trade was originally invoiced in US dollars, renminbi, another vehicle currency or the currency of the destination. We turn to the customs records of Her Majesty’s Revenue and Customs (HMRC) in the United Kingdom to answer this question for one of China’s major destination markets. We interpret the widespread prevalence of dollar invoicing for a country that issues its own vehicle currency as suggestive that Chinese exports to other countries, including those that do not issue vehicle currencies, are likely predominately invoiced in US dollars.

Since 2010, HMRC has recorded the invoicing currency for the vast majority of import and export transactions between the UK and non-EU trading partners. The reporting requirements for invoice currency are described in UK Non-EU Trade by declared currency of Invoice (2016), published 25 April 2017. See page 7: “Only data received through the administrative Customs data collection has a currency of invoice declared... For Non-EU import trade, businesses must submit the invoice currency when providing customs declarations. However, 5.0 per cent of Non-EU import trade value [in 2016] did not have a currency... This was accounted for by trade reported through separate systems, such as parcel post and some mineral fuels. For Non-EU export trade, businesses are required to declare invoice currency for declarations with a value greater than £100,000. As a result of this threshold and trade collected separately (reasons outlined above) 10.1 per cent of Non-EU export trade [in 2016] was declared without a currency.”

Figure 3 presents the shares of import transactions and import value into the UK from China by invoicing currency. Results are reported for three currencies, the euro (EUR), pound sterling (GBP), and the US dollar (USD). All transactions that use another currency to invoice UK imports from China, for example, the Swiss franc, Japanese yen or Chinese renminbi, are aggregated into the category “Other.” In each graph, the dark bar refers to the share of transactions and the light grey bar refers to the share of import value reported in the relevant currency.

The first point to note is that virtually all of the UK’s imports from China are invoiced in one of three major currencies: the pound sterling (GBP), the US dollar (USD), or the euro (EUR). Very little trade is invoiced in any other currency, including the Chinese renminbi.

The second striking point is that the most important currency for Chinese exports to the UK is the US dollar. The dollar’s prominence as the invoicing currency of choice for Chinese exports to the UK rose over 2010-2016 with the share of import value growing from 71.1% to 77.7%. The share of transactions invoiced in US dollars was stable at around 83% throughout 2010-2016.

50 The reporting requirements for invoice currency are described in UK Non-EU Trade by declared currency of Invoice (2016), published 25 April 2017. See page 7: “Only data received through the administrative Customs data collection has a currency of invoice declared... For Non-EU import trade, businesses must submit the invoice currency when providing customs declarations. However, 5.0 per cent of Non-EU import trade value [in 2016] did not have a currency... This was accounted for by trade reported through separate systems, such as parcel post and some mineral fuels. For Non-EU export trade, businesses are required to declare invoice currency for declarations with a value greater than £100,000. As a result of this threshold and trade collected separately (reasons outlined above) 10.1 per cent of Non-EU export trade [in 2016] was declared without a currency.”

51 To construct this figure, we begin with the universe of UK import transactions for goods originating from China over 2010-2016. Then, we aggregate all transactions within a year that are reported for a firm-CN08 product-quantity measure-currency quadruplet to an annual observation for that quadruplet. The variable “quantity measure” records whether a transaction for a CN08 product is reported in kilograms or a supplementary quantity unit like “items” or “pairs.” This leaves us with 2.004 million annual transactions which we use to construct figure 3.

52 We do not report the number of transactions for which the currency is not reported; the number of transactions with no currency reported falls below HMRC Datalab’s threshold rule of firms in at least one year and is, for confidentiality reasons, omitted from the figure.

53 See also Goldberg and Tille (2008) and Goldberg and Tille (2016) who document relatively large shares of
Over this same period, the pound’s importance as an invoicing currency for imports from China fell. While the share of transactions held steady at 10-12% over the period, the share of import value from China invoiced in sterling fell from a high of 21.9% in 2010 to a low of 16.0% by 2016. The importance of the euro as an invoicing currency for Chinese exports to Britain was low throughout 2010-2016.

In figure 4 we present information on the currency of invoicing for UK exports to China. Firms are only required to report the currency of invoicing for export transactions whose value exceeds £100,000. Thus, the share of export transactions and value for which no invoicing currency is reported is sizeable. In figure 4, these are indicated by “NR.”

In almost all years the British pound sterling is the most important currency of invoicing for exports to China, both in transaction and value terms. Interestingly, the sterling does not dominate invoicing of exports entirely; substantial shares of exports are invoiced in US dollars. The euro appears to play a minor role and other currencies, including the Chinese renminbi, are rarely used.

The proportion of Britain’s exports for which no currency is reported declines over time. Pre-exports invoiced in dollars for many countries.

---

54 To construct figure 4 we follow the same procedure described above for imports. We arrive at approximately 266 thousand annual transactions which we use to construct the figure.
Figure 4: Invoicing currencies for UK exports to China

Black: Share of Transactions; Grey: Share of Trade Value
Source: Calculations based on HMRC administrative datasets.

Sumably this is related to an increase in the nominal value of trade transactions such that a greater proportion exceed the £100,000 reporting requirement over time.

This evidence is relevant to our empirical analysis to follow, insofar as a firm that invoices in a vehicle currency, say dollars, also prices its good in that currency. Suppose that the firm sets one single price for its product in dollars: this practice (arguably maximizing the markup relative to global demand) would rule out destination specific adjustment in markups. In this case, our TPSFE estimation should yield insignificant results. The same would be true if firms set different dollar prices across markets (in line with evidence of deviations from the law of one price), but do not adjust them in response to fluctuations in the exchange rate.

This suggests that our TPSFE estimator of markup elasticities can provide evidence on a relevant implication of what Gopinath has dubbed the ‘International Price System.’ Specifically, our empirical findings can inform us about the possibility of dollar invoicing translating into a ‘reference price system’ in which firms do not exploit market-specific demand elasticities, but price in relation to global demand. If a reference price system dominates, we would expect to observe firms setting one prevailing price in the global market for manufactured goods as they do for commodities.
D.4 Price Changes and Trade Pattern Dummies

In this subsection, we show how we build our (unbalanced) panel. We will rely on an example to explain how we identify price changes at the firm-product destination level and trade patterns across destinations at the firm-product level in the data.

Consider a firm exporting a product to five countries, A through E, over 6 time periods. In the following matrix, rows are time periods and columns are destination countries. Empty elements in the matrix indicate that there was no trade.

\[
\begin{array}{cccc}
\text{t} = 1 & A & B & \\
\text{t} = 2 & A & B & C & E \\
\text{t} = 3 & A & B & C & D \\
\text{t} = 4 & A & C & D & E \\
\text{t} = 5 & A & B & C & \\
\text{t} = 6 & A & B & C & D \\
\end{array}
\]

The following matrix records prices by destination country and time:

\[
\begin{bmatrix}
  p_{A,1} & p_{B,1} & \cdot & \cdot & \cdot \\
p_{A,2} & p_{B,2} & p_{C,2} & \cdot & p_{E,2} \\
p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & \cdot \\
p_{A,4} & \cdot & p_{C,4} & p_{D,4} & p_{E,4} \\
p_{A,5} & p_{B,5} & p_{C,5} & \cdot & \cdot \\
p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdot \\
\end{bmatrix}
\]

Suppose the pricing currency is the dollar and we want to identify price changes in dollars. First, we compare prices denominated in dollars (vertically) at the firm-product-destination level as illustrated in the following figure. Price changes less than 5% are marked with “x”.

We then set the first batch of individual prices associated with a price changes below \( \pm 5\% \) \((p_{B,5}, p_{C,4}, p_{D,4}, p_{E,4})\) to missing (i.e., these are the latter of the level price entries used in constructing the change). This gives

\[
\begin{pmatrix}
  p_{A,1} & p_{B,1} & \cdots & \cdots \\
  p_{A,2} & p_{B,2} & p_{C,2} & \cdots \\
  p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & p_{E,3} \\
  p_{A,4} & \cdots & \cdots & \cdots \\
  p_{A,5} & \cdots & p_{C,5} & \cdots \\
  p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & \cdots
\end{pmatrix}
\]

Note that we did not treat \( p_{C,5} \) as missing at this stage. This is because \( |p_{C,5} - p_{C,3}| \) could be > 5\% even if both \( |p_{C,4} - p_{C,3}| < 5\% \) and \( |p_{C,5} - p_{C,4}| < 5\% \)\(^{55}\). Rather, we repeat the above step using the remaining observations as illustrated below.

\[^{55}\text{Variables are in logs.}\]
In this example, we indeed find $|p_{C,5} - p_{C,3}| > 0$ and the remaining pattern is given as follows. As no prices are sticky, we can stop the iteration.\textsuperscript{56} Note that as no price changes can be formulated for the single trade record $p_{E,2}$, this observation is dropped from our sample.

\[
\begin{bmatrix}
  p_{A,1} & p_{B,1} & . & . & . \\
  p_{A,2} & p_{B,2} & p_{C,2} & . & . \\
  p_{A,3} & p_{B,3} & p_{C,3} & p_{D,3} & . \\
  p_{A,4} & . & . & . & . \\
  p_{A,5} & . & p_{C,5} & . & . \\
  p_{A,6} & p_{B,6} & p_{C,6} & p_{D,6} & .
\end{bmatrix}
\]

Now we have identified the universe observations with price changes. The next step is to formulate the trade pattern dummy.

\[
\begin{align*}
t = 1 & \quad A \quad B \\
t = 2 & \quad A \quad B \quad C \\
t = 3 & \quad A \quad B \quad C \quad D \\
t = 4 & \quad A \quad C \\
t = 5 & \quad A \quad C \\
t = 6 & \quad A \quad B \quad C \quad D
\end{align*}
\]

In this example, we find 5 trade patterns, i.e., $A - B$, $A - B - C$, $A - B - C - D$, $A$, $A - C$, but only one pattern, $A - B - C - D$, which appears at least two times. To compare the change in relative prices across destinations, we require the same trade pattern be observed at least two times in the price-change-filtered dataset.\textsuperscript{57} In the example presented above, only prices within the trade pattern $A - B - C - D$ will be compared because it is the only unique pattern to appear two times. In the real customs database with hundreds of thousands of firms, each trade pattern typically is associated with many firm-product-time triplets. The destination demeaned (relative) price is first constructed at the firm-product-time level (i.e., this is the first step of in TPSFE estimation procedure) and regressions are then run adding trade pattern fixed effects\textsuperscript{58} (i.e., this is the second step of the TPSFE estimator).

\textsuperscript{56} In the real dataset, the algorithm often needs to iterate several times before reaching this stage.

\textsuperscript{57} Essentially, by formulating trade pattern fixed effects, we are restricting the comparison within a comparable environment. Firms switch trade patterns for a reason. Restricting the analysis to the same trade pattern also controls for other unobserved demand factors affecting the relative prices.

\textsuperscript{58} To construct trade pattern fixed effect dummies, we prefix the destination country in front of the trade pattern, e.g. $A - A - B - C - D$, $B - A - B - C - D$, $C - A - B - C - D$, $D - A - B - C - D$. Prefixing the destination country code ensures the “destination-trade pattern” comparison of prices and exchange rates.
<table>
<thead>
<tr>
<th>Year</th>
<th>Country</th>
<th>Value</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>2001</td>
<td>Germany</td>
<td>7957</td>
<td>.43</td>
</tr>
<tr>
<td></td>
<td>Indonesia</td>
<td>28543</td>
<td>.49</td>
</tr>
<tr>
<td></td>
<td>Italy</td>
<td>2416699</td>
<td>.47</td>
</tr>
<tr>
<td></td>
<td>Thailand</td>
<td>6900</td>
<td>.38</td>
</tr>
<tr>
<td></td>
<td>Vietnam</td>
<td>9391</td>
<td>.49</td>
</tr>
<tr>
<td>2002</td>
<td>Indonesia</td>
<td>69241</td>
<td>.48</td>
</tr>
<tr>
<td></td>
<td>Italy</td>
<td>1415535</td>
<td>.54</td>
</tr>
<tr>
<td></td>
<td>Latvia</td>
<td>9302</td>
<td>.53</td>
</tr>
<tr>
<td></td>
<td>Philippines</td>
<td>9126</td>
<td>.52</td>
</tr>
<tr>
<td></td>
<td>South Korea</td>
<td>8908</td>
<td>.48</td>
</tr>
<tr>
<td>2003</td>
<td>Germany</td>
<td>47924</td>
<td>.49</td>
</tr>
<tr>
<td></td>
<td>Japan</td>
<td>54450</td>
<td>.36</td>
</tr>
<tr>
<td></td>
<td>Philippines</td>
<td>9126</td>
<td>.52</td>
</tr>
</tbody>
</table>

Table 18: A real data example of changing trade patterns: Exports of tomato paste (HS 20029010) by the firm with identifier 6512910023
### D.5 Data cleaning process and the number of observations

Table 19: Stage 0 - Raw

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>8-digit HS Codes</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>108,465,375</td>
<td>246</td>
<td>10,002</td>
<td>581,141</td>
</tr>
</tbody>
</table>

Table 20: Stage 1 - Drop exports to the U.S. and Hong Kong

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>8-digit HS Codes</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>92,308,538</td>
<td>244</td>
<td>9,959</td>
<td>545,175</td>
</tr>
</tbody>
</table>

Table 21: Stage 2 - Drop if the destination identifier, product identifier or value of exports is missing; Drop duplicated company names

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>8-digit HS Codes</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>92,177,750</td>
<td>243</td>
<td>9,954</td>
<td>545,133</td>
</tr>
</tbody>
</table>

Table 22: Stage 3 - Collapse at firm-product-destination-year level; integrating 17 eurozone countries into a single economic entity

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>8-digit HS Codes</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>83,439,048</td>
<td>227</td>
<td>9,954</td>
<td>545,133</td>
</tr>
</tbody>
</table>

A product is defined as 8-digit HS code + a form of commerce dummy + a CCHS classification dummy. More precisely, this could be described as a variety but we used the term product throughout the paper.

Table 23: Stage 4 - Drop observations if bilateral exchange rates or destination CPI is missing

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>8-digit HS</th>
<th>6-digit HS</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>77,511,443</td>
<td>157</td>
<td>9,929</td>
<td>5,867</td>
<td>532,530</td>
</tr>
</tbody>
</table>
Table 24: Stage 5 - Filtering price changes (in logs, denominated in RMB) < 0.05 at the firm-product-destination level following the method described by D.4

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>Products</th>
<th>6-digit HS</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>72,792,147</td>
<td>157</td>
<td>20,347</td>
<td>5,867</td>
<td>532,530</td>
</tr>
</tbody>
</table>

Our method uses both destination and time variations to identify markup and quantity responses to prices and exchange rate shocks. We drop single-year or single-destination observations.

Table 25: Stage 6 - Drop single-destination firm-product-year triplets

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>Products</th>
<th>6-digit HS</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>50,355,418</td>
<td>157</td>
<td>17,258</td>
<td>5,446</td>
<td>356,541</td>
</tr>
</tbody>
</table>

Table 26: Stage 7 - Drop single-year firm-product-destination triplets

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>Products</th>
<th>6-digit HS</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>23,750,519</td>
<td>154</td>
<td>14,611</td>
<td>5,051</td>
<td>238,610</td>
</tr>
</tbody>
</table>

Finally, we drop “single-year firm-product-trade pattern triplets.” Including these observations will not change estimates of our proposed estimators but over-report the number of observations in the estimation sample.

Table 27: Stage 8 - Formulating trade pattern; Drop single-year firm-product-trade pattern triplets

<table>
<thead>
<tr>
<th>Observations</th>
<th>Destinations</th>
<th>Products</th>
<th>6-digit HS</th>
<th>Firms</th>
<th>Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of unique values</td>
<td>5,940,011</td>
<td>154</td>
<td>14,172</td>
<td>5,007</td>
<td>209,499</td>
</tr>
</tbody>
</table>

D.6 Macroeconomic Data

Macroeconomic variables on nominal bilateral exchange rates, CPI of all destination countries (normalized so that CPI=100 in 2010 for all series), real GDP (constant 2005 US dollars), the import to GDP ratio come from the World Bank. We construct the nominal bilateral exchange

\footnote{These observations are entirely absorbed by our fixed effects and do not provide additional variation for identification. After applying destination demean at the firm-product-time level and trade pattern fixed effects, the residual variation is zero for all dependent and independent variables.}
rate in renminbi per unit of destination currency from China’s official exchange rate (rmb per US$) and each destination country’s official exchange rate in local currency units per US$ (all series are the yearly average rate). These variables are available for 154 destination countries in our sample.

In our empirical analysis, we focus on nominal rather than real bilateral exchange rates. Estimations using real exchange rates implicitly impose a one-to-one linear relationship between each nominal bilateral exchange rate and the ratio of CPI indices (i.e., destination CPI/origin CPI). Real exchange rate series which embed this restriction are highly correlated with nominal exchange rates. Since nominal exchange rate series are significantly more volatile over time than the ratio of CPI indices, movements in the real exchange rate are primarily driven by fluctuations in nominal exchange rates. It is not clear if restricting these two variables with significantly different volatilities into a one-to-one linear relationship is justified in exchange rate pass through studies. Throughout our analysis, we enter nominal bilateral exchange rates and destination CPI index as two separate variables.

As we discussed in previous sections, taking time differences in an endogenously unbalanced panel tends to make the unobserved marginal cost uncontrollable and introduce potential biases. In all our regressions, we enter variables in logged levels. A concern of using logged levels rather than time differences is that nominal series, such as exchange rates and CPI indices, cannot be compared directly across countries. In solving this compatibility problem, it is useful to think of the nominal series as a compatible measure plus an unobserved destination specific drift, i.e.,

\[ e_{dt}^{\text{nominal}} = e_{dt}^{\text{compatible}} + \mu_d. \]

Due to our trade pattern fixed effects, our proposed approach is robust to this type of destination specific drift, which enables us to correctly disentangle the effect of nominal exchange rate fluctuations from destination CPI movements.

### D.7 Additional Information on the CCHS Classification

To illustrate how measure words encode meaning in Chinese, consider the problem of counting three small objects. Chinese grammar requires the use of a measure word between the number and the noun being counted. Thus, to say “three ballpoint pens,” or “three kitchen knives,” one would say the English equivalent of “three long-thin-cylindrical-objects [zhī, 乢] ballpoint pens” and “three objects-with-a-handle [bà, 把] kitchen knives.”\(^{60}\) Both of these objects, ballpoint pens and kitchen knives, are measured with count classifiers (zhī and bà, respectively) and are, in

\(^{60}\) English uses measure words; “two dozen eggs” and “a herd of cattle” are two examples. The difference lies in the extent to which unique measure words exist for Chinese nouns and the fact that proper Chinese grammar always requires the use of the appropriate measure word when counting.
our classification, high differentiation goods. In contrast, products reported with mass classifiers including kilograms (cereal grains, industrial chemicals), meters (cotton fabric, photographic film), and cubic meters (chemical gases, lumber) are low differentiation goods. Because measure words encode physical features of the object being counted, they allow us to identify when statistical reporting is for a high versus low differentiation good. According to Cheng and Sybesma (1999), “...the distinction between the two types of classifiers is made with explicit reference to two different types of nouns: nouns that come with a built-in semantic partitioning and nouns that do not – that is, count nouns and mass nouns.” While it is possible that our proposed system could lead to some amount of mis-classification because there are some count nouns which exhibit low levels of differentiation and some mass nouns which are quite differentiated, a Chinese-linguistics-based approach to goods classification is still valuable for two reasons. First, nouns with built-in semantic partitioning such as televisions, microscopes and automobiles are high differentiation goods regardless of whether their trade is reported in metric tonnes or units. This is a key advantage of relying on Chinese measure words to classify tradeable goods: measure words clearly identify objects that inherently are semantically partitioned (i.e. are distinct objects), relative to goods that exist as undifferentiated masses. Second, the choice of the measure word is predetermined in the minds of Chinese speakers by grammatical rules that have existed for centuries. This choice is clearly exogenous to and predates modern statistical reporting systems.\(^{61}\)

To illustrate the variety of count classifiers used for similar objects, note that “Women’s or girls’ suits of synthetic fibres, knitted or crocheted” (HS61042300) and “Women’s or girls’ jackets & blazers, of synthetic fibres, knitted or crocheted” (HS61043300) are measured with two distinct Chinese count classifiers, “套” and “件,” respectively. Further, table 28 documents the intrinsic information content of the measurement units for HS04 product groups 8211 and 8212. The Chinese language descriptions of all of these HS08 products conveys the similarity across products; each Chinese description contains the Chinese character ‘dao’ (刀), which means ‘knife’ and is a part of longer compound words including table knife and razor. Interestingly, three different Chinese count classifiers, “tào, 套,” “bā, 把,” and “piàn, 片,” are used to count sets of knives (HS82111000), knives and razors (HS82119100 - HS82121000), and razor blades (HS82122000),

\(^{61}\)A subtle distinction arises between the statistical reporting of trade data in Japan and China. The Japanese language also requires the use of measure words, aka ‘counters,’ when counting. However, documentation for Japanese trade declarations instructs that the measurement unit “NO” (the English abbreviation for number) should be used for reporting quantity and explains that this Western measure word subsumes 11 Japanese language measure words (個, 本, 枚, 頭, 羽, 匹, 台, 呎, 機, 隻, 着). These instructions on Japanese Customs declarations validate our approach for China because these 11 Japanese measure words are linguistically similar to Chinese count classifiers. However, because the reporting is based on a Western word, the choice of a measurement unit in Japanese data might not be exogenously driven by the structure of the Japanese language. Thus, there is a reason for basing the classification of goods using linguistic information on Chinese rather than Japanese customs data. We thank Taiji Furusawa, Keiko Ito, and Tomohiko Imui for answering our questions about the use of measure words in Japanese trade data.
respectively.

Table 28: Examples of count classifiers in the Chinese Customs Database

<table>
<thead>
<tr>
<th>Quantity Measure</th>
<th>HS08 Code</th>
<th>English Description</th>
<th>Chinese Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>tào, 套</td>
<td>82111000</td>
<td>Sets of assorted knives</td>
<td>成套的刀</td>
</tr>
<tr>
<td>bǎ, 把</td>
<td>82119100</td>
<td>Table knives having fixed blades</td>
<td>刃面固定的餐刀</td>
</tr>
<tr>
<td>bǎ, 把</td>
<td>82119200</td>
<td>Other knives having fixed blades</td>
<td>其他刃面固定的刀</td>
</tr>
<tr>
<td>bǎ, 把</td>
<td>82119300</td>
<td>Pocket &amp; pen knives &amp; other knives with folding blades</td>
<td>可换刃面的刀</td>
</tr>
<tr>
<td>bǎ, 把</td>
<td>82121000</td>
<td>Razors</td>
<td>剃刀</td>
</tr>
<tr>
<td>piàn, 片</td>
<td>82122000</td>
<td>Safety razor blades, incl razor blade blanks in strips</td>
<td>安全刀片, 包括未分开的刀片</td>
</tr>
</tbody>
</table>

The most frequently used mass classifier is kilograms. Examples of other mass classifiers include meters for “Knitted or crocheted fabric of cotton, width ≤ 30cm” (HS60032000), square meters for “Carpets & floor coverings of man-made textile fibres” (HS57019010), and liters for “Beer made from malt” (HS22030000).

In table 29, we provide a breakdown of our CCHS classification within the UN’s Broad Economic Categories (BEC) of intermediate, consumption and other goods. The majority of intermediate goods are low differentiation and the majority of consumption goods are high differentiation, but all BEC groups include both high differentiation and low differentiation goods.
Table 29: Classification of differentiated goods: CCHS vs. BEC

(a) Share of goods by classification: observation weighted

<table>
<thead>
<tr>
<th>Corsetti-Crowley-Han-Song (CCHS)</th>
<th>Low Differentiation / (Mass nouns)</th>
<th>High Differentiation / (Count nouns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate</td>
<td>29.8</td>
<td>2.7</td>
</tr>
<tr>
<td>Consumption</td>
<td>14.3</td>
<td>20.1</td>
</tr>
<tr>
<td>Other†</td>
<td>15.0</td>
<td>18.1</td>
</tr>
<tr>
<td></td>
<td>59.1</td>
<td>40.9</td>
</tr>
</tbody>
</table>

(b) Share of goods by classification: value weighted

<table>
<thead>
<tr>
<th>Corsetti-Crowley-Han-Song (CCHS)</th>
<th>Low Differentiation / (Mass nouns)</th>
<th>High Differentiation / (Count nouns)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intermediate</td>
<td>26.0</td>
<td>3.9</td>
</tr>
<tr>
<td>Consumption</td>
<td>8.6</td>
<td>14.0</td>
</tr>
<tr>
<td>Other†</td>
<td>12.6</td>
<td>34.9</td>
</tr>
<tr>
<td></td>
<td>47.2</td>
<td>52.8</td>
</tr>
</tbody>
</table>

Notes: Share measures are calculated based on Chinese exports to all countries including Hong Kong and the United States during periods 2000-2014. †: The “Other” category refers to capital goods and unclassified products by BEC classification, such as nuclear weapons.

For twenty industrial sectors, Table 30 reports the share of products in each sector that are classified as high differentiation according to the Corsetti, Crowley, Han, and Song (CCHS) classification. For the 36 measure words in our estimation dataset, we categorize goods measured with the 24 count classifiers as high differentiation, while goods measured with 12 mass classifiers are treated as low differentiation.\(^{62}\) Column one lists the HS chapters that define the sector. The second column provides the sector’s share in China’s total exports over 2000-2014. Quantitatively, important export sectors with large shares of high differentiation goods include optical and photographic equipment (79.7 percent), machinery and mechanical appliances (73.1 percent), textiles and apparel (68.4 percent), vehicles and aircraft (66.1 percent), stone and plaster articles (65.0 percent), leather goods (58.6 percent), and plastics and rubber articles (15.0 percent). The share of

\(^{62}\)We thank Prof. Lisa Lai-Shen Cheng for her feedback on our classification of measure words from the Chinese Customs Database into count and mass classifiers.
Table 30: CCHS product classification across sectors

<table>
<thead>
<tr>
<th>Sector (HS chapters)</th>
<th>Sector’s share of total exports</th>
<th>Value share of CCHS high differentiation products within sector</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-5 Live animals; animal products</td>
<td>0.8</td>
<td>4.0</td>
</tr>
<tr>
<td>6-14 Vegetable products</td>
<td>1.0</td>
<td>0.6</td>
</tr>
<tr>
<td>15 Animal/vegetable fats</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>16-24 Prepared foodstuffs</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>25-27 Mineral products</td>
<td>2.1</td>
<td>0.0</td>
</tr>
<tr>
<td>28-38 Products of chemical and allied industries</td>
<td>4.6</td>
<td>0.2</td>
</tr>
<tr>
<td>39-40 Plastics/rubber articles</td>
<td>3.4</td>
<td>15.0</td>
</tr>
<tr>
<td>41-43 Rawhides/leather articles, furs</td>
<td>1.6</td>
<td>58.6</td>
</tr>
<tr>
<td>44-46 Wood and articles of wood</td>
<td>0.8</td>
<td>0.5</td>
</tr>
<tr>
<td>47-49 Pulp of wood/other fibrous cellulosic material</td>
<td>0.8</td>
<td>0.0</td>
</tr>
<tr>
<td>50-63 Textile and textile articles</td>
<td>13.2</td>
<td>68.4</td>
</tr>
<tr>
<td>64-67 Footwear, headgear, etc.</td>
<td>2.9</td>
<td>43.5</td>
</tr>
<tr>
<td>68-70 Misc. manufactured articles</td>
<td>1.8</td>
<td>3.2</td>
</tr>
<tr>
<td>71 Precious or semiprec. stones</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>72-83 Base metals and articles of base metals</td>
<td>7.7</td>
<td>1.9</td>
</tr>
<tr>
<td>84-85 Machinery and mechanical appliances, etc.</td>
<td>42.2</td>
<td>73.1</td>
</tr>
<tr>
<td>86-89 Vehicles, aircraft, etc.</td>
<td>4.7</td>
<td>66.1</td>
</tr>
<tr>
<td>90-92 Optical, photographic equipment etc.</td>
<td>3.5</td>
<td>79.7</td>
</tr>
<tr>
<td>93 Arms and ammunition</td>
<td>0.0</td>
<td>82.5</td>
</tr>
<tr>
<td>94-96 Articles of stone, plaster, etc.</td>
<td>6.0</td>
<td>65.0</td>
</tr>
<tr>
<td>97 Works of art, antiques</td>
<td>0.1</td>
<td>60.8</td>
</tr>
</tbody>
</table>

Source: Compiled by the authors from exports of Chinese Customs Database, 2000-2014, using the Corsetti, Crowley, Han and Song (CCHS) classification.

High differentiation products across sectors varies widely, but lines up with our priors. Machinery and mechanical appliances and vehicles and aircraft are dominated by CCHS high differentiation goods while virtually all chemicals and base metal products are low differentiation.
D.7.1 Rauch classification for China exports

In order to provide a Rauch classification for each product in the Chinese Customs Database, it was necessary to concord the SITC Rev. 2 product codes from Rauch’s classification to HS06 product codes used in the Chinese Customs Database.

Table 31: 6-digit HS code matching rate with Rauch classification using HS2002toSITC2 concordance table and the conservative version of Rauch classification

<table>
<thead>
<tr>
<th>Number of 6-digit HS codes</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matched (Unique Rauch Classification for Each HS Code)</td>
<td>4,589</td>
</tr>
<tr>
<td>Unmatched (Multiple Rauch Classifications for Each HS Code)</td>
<td>1,272</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>5,861</strong></td>
</tr>
</tbody>
</table>

Table 32: 6-digit HS code matching rate with Rauch classification using HS2007toSITC2 concordance table and the liberal version of Rauch classification

<table>
<thead>
<tr>
<th>Number of 6-digit HS codes</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Matched (Unique Rauch Classification for Each HS Code)</td>
<td>4,438</td>
</tr>
<tr>
<td>Unmatched (Multiple Rauch Classifications for Each HS Code)</td>
<td>1,046</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>5,484</strong></td>
</tr>
</tbody>
</table>

E Further Analysis: Firms, Markups and Market Power

The intense competition that Chinese imports have brought to high income countries has spawned research into how this enhanced global competitive pressure has influenced corporates’ decisions to upgrade their product mix (Bernard, Jensen and Schott (2006)), innovate (Bloom, Draca and Van Reenen (2016)), lay off workers (Autor, Dorn and Hanson (2013), Pierce and Schott (2016)), and outsource to lower wage markets (Pierce and Schott (2016)). Business people and economists speak of the problem of “the China price,” the low price of Chinese merchandise that exporters
from other markets and domestic import-competing firms must match if they want to survive. In section 4.2, we provided evidence that strategic pricing-to-market and markup adjustments are more prominent in the markets for high differentiation goods, especially consumption goods, while quantitatively less pronounced in the markets for low differentiation manufactured goods with higher degrees of competition. We now dig deeper into the Chinese Customs Database, and examine how to square our results so far with the evolving identity of Chinese exporters.

The Chinese economy is widely understood to be a hybrid in which competitive, market-oriented private firms operate alongside large, state-owned enterprises (SOEs). Looking at exports, the picture is actually more complex. Quantitatively, the dominant role in exports is played by firms that are wholly foreign owned or are Sino-foreign joint enterprises—the leading types in a group that we label foreign-invested enterprises (FIEs).

Reflecting their ownership/type, firms are likely to have different cost structures and face different demand elasticities. A popular view of SOEs and FIEs is that they both have relatively easy access to capital, but likely differ in the extent to which they rely on imported intermediates in production. Conversely, private firms are widely seen as facing a tighter financing constraint and, relative to FIEs, a lower level of integration with global supply chains. Moreover, reflecting different rates of entry, the average size of a firm also differs across these groups—with private enterprises being smaller. Last but not least, being more integrated in supply chains, FIEs may engage in transfer pricing. In light of these considerations, we might expect SOEs, FIEs and private firms to endogenously end up producing different products, using different production processes, and possibly targeting different markets. Our question is whether, due to these factors, observable differences in pricing, markup adjustments and cross-destination quantity adjustments map into firms’ registration types.

E.1 The evolution of China’s exports by different types of firms

In figure 5, we lay out some basic facts about the evolution of different types of firms among Chinese exporters. In the Chinese Customs Database, firms report their registration type in one of the following eight categories: state-owned enterprise, Sino-foreign contractual joint venture, Sino-foreign equity joint venture, wholly foreign owned enterprise, collective enterprise, private enterprise, individual business, and “other” enterprise. We combine Sino-foreign contractual joint ventures, Sino-foreign equity joint ventures, and wholly foreign owned enterprises into a single category - foreign invested enterprises (FIEs). Firms with other ownership structures, including collectives, individual businesses, and “other” enterprises, are lumped together under the descriptor “Other” enterprises.

Figure 5: The changing face of Chinese exporters, 2000-2014

Note: Calculations based on the universe of all exporters from the customs database of China. Three types of foreign invested enterprises are reported in our dataset, namely wholly foreign owned enterprises (coded as “4”), sino-foreign joint ventures by jointed equity (coded as “3”) and by contractual arrangements that specify the division of tasks and profits (coded as “2”). The last type is quantitatively small in firm number and trade values.
A well-known fact is the extraordinary rate of entry into export activity by private enterprises. This is apparent in the top panel of the figure. From being a small and neglectable group in 2000, the number of private enterprises directly exporting goods from China to the rest of the world rose to over 200,000 by 2014.\textsuperscript{64} Perhaps less known and understood, however, is the economic weight of a different category of exporters from China, the foreign-invested enterprises (FIEs), also highlighted by our figure. After a slow and steady rise between 2000 and 2006, their number stabilized at about 75,000 firms—dwarfing the presence of state-owned enterprises (SOEs). Indeed, in spite of the attention paid to them by the media, there were only 10,000 registered SOEs at the start of our sample period. This number gradually fell over time, as successive policy initiatives favored their privatization, or led some of them to exit from foreign markets (top panel, figure 5).

The key message from the top panel of figure 5 is reinforced by the analysis of export values and shares by different types of firms, shown in the bottom panel. By export value and share of total exports, the most important single group of exporters from China is that of foreign-invested enterprises. In 2014, the value of their exports was over US $1 trillion (bottom left panel of figure 5). Over the period, exports from China that originated from firms that are wholly or partially owned by foreigners fluctuated between 45 and 58% of China’s total exports.\textsuperscript{65}

Conversely, the weight of SOEs, which were essentially at par with FIEs in 2000, declined dramatically from 2000 to 2007 and then settled into a slow and steady negative trend (bottom left panel, figure 5). This is clear evidence that the role of SOEs in foreign trade has been far less dynamic than that of other types of firms. However, the diminishing weight of SOEs in foreign trade has been more than made up by private firms—reflecting both entry of new firms into export markets and privatization of SOEs. By the end of the sample, private firms account for a striking 40% of Chinese exports. We stress nonetheless that this large shift in export shares between SOEs and private firms has not (so far at least) dented the share of exports by FIEs, which has remained quite stable over our sample.

As shown below, against this evolution in the number of exporters and export shares by ownership, there are significant differences in strategic pricing—markup elasticities diverge strikingly across FIEs, SOEs and private firms. We argue that evidence on these differences is key to understanding the dynamic evolution of Chinese entrepreneurs in international markets.

\textsuperscript{64}At the start of our sample period, export activity was highly regulated in China with most rights to export held by SOEs—only a very limited number of private enterprises were able to export directly. The result of this was that in the earlier years post-2000 private enterprises desiring to export their merchandise exported through SOEs.

\textsuperscript{65}The importance of foreign involvement in Chinese exports has previously been documented by Koopman, Wang and Wei (2014). Based on an accounting framework methodology and product-level trade flows, they show that 29.3 percent of Chinese export value comes from foreign, rather than domestic Chinese, value-added. This is not inconsistent with our estimates; our complementary contribution is to document foreign engagement based on ownership of exporting firms, rather than through the origin of the value-added content of exported goods.
E.2 The market power of Chinese and foreign firms

Evidence on price, markup and supply elasticities by firm type is presented in table 33. Relative to other Chinese exporters, foreign-invested enterprises (FIEs) stand out in that, across destination markets, they make larger adjustments to their renminbi export prices (0.49), have moderately elastic markups (0.21), and have an inelastic within-firm cross market supply elasticity (CMSE) (see table 33, row 2, columns (1), (2) and (4)). The high estimate of the Chinese export price elasticity of 0.49 implies that the ERPT into import prices in foreign currency is relatively low (51%), reflecting that these firms are more actively pursuing local currency price stabilization than other groups of firms. Notably, markup adjustment accounts for two fifths (0.21/0.49) of this incomplete pass through into import prices.

Relative to FIEs, the export price response to exchange rates by SOEs is smaller, 0.32 (see row 1, column (1) of table 33), implying a much higher pass through into import prices, as high as 68%. While SOEs make similar markup adjustments compared to FIEs in absolute terms, the share of markup adjustment to incomplete pass through is higher (0.22/0.32 versus 0.21/0.49). Like FIEs, SOEs have an extremely low cross market supply elasticity, 0.47 (row 1, column (4)). This evidence together suggests that both FIEs and SOEs are endowed with a high degree of market power which enables them to exploit market segmentation and strategically price-to-market.

The picture is totally different for private enterprises. On average, these firms adjust their export prices far less than either SOEs or FIEs—by a mere 1 percent in response to a 10 percent appreciation (see row 3, column (1) of table 33). Of this, a modest 40 percent is due to a tiny, yet statistically significant, markup adjustment by destination (0.04/0.10). Pass through into foreign import prices is as high as 90 percent. What is truly extraordinary is the within-firm cross market supply elasticity: for private firms, a one percent increase in the relative markup caused by a bilateral exchange rate appreciation leads to a 4.7 percent increase in the relative quantity sold in that destination. This is evidence that, on average, Chinese private firms aggressively chase profit opportunities across destination markets by expanding quantities, but make only small markup adjustments in response to destination-specific currency movements.\footnote{This type of highly responsive substitution of export value (p*q) across markets has also been identified in the context of destination-specific tariff increases and product-level trade flows by Bown and Crowley (2006) and Bown and Crowley (2007). In the trade flow and tariff literature, it is referred to as “trade deflection.” A similar cross-destination supply response of capital flows has been identified by Giordani, Ruta, Weisfeld and Zhu (2017).}

The second and third panels of table 33 break down the estimates by firm type, distinguishing between high and low differentiation goods. Two key results stand out. First, within each class of firms, the number of exporters of either high and low differentiation goods is large (see the number of observations for each sample in column (5)): there is no apparent specialization by firm type. This means that the different pricing behavior noted in our comments about the top
Table 33: Pricing Strategies by Firm Registration Types (2006 – 2014)

<table>
<thead>
<tr>
<th></th>
<th>Price Elasticity</th>
<th>Markup Elasticity</th>
<th>Naive Reg.</th>
<th>CMSE</th>
<th>n. of obs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State-owned Enterprises</td>
<td>0.32***</td>
<td>0.22***</td>
<td>-0.70***</td>
<td>0.47***</td>
<td>644,385</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.15)</td>
<td></td>
</tr>
<tr>
<td>Foreign Invested Enterprises</td>
<td>0.49***</td>
<td>0.21***</td>
<td>-0.69***</td>
<td>0.22</td>
<td>1,053,734</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Private Enterprises</td>
<td>0.10***</td>
<td>0.04***</td>
<td>-0.70***</td>
<td>4.72***</td>
<td>3,010,176</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.94)</td>
<td></td>
</tr>
<tr>
<td><strong>High Differentiation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State-owned Enterprises</td>
<td>0.46***</td>
<td>0.39***</td>
<td>-0.69***</td>
<td>0.38***</td>
<td>283,697</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.00)</td>
<td>(0.14)</td>
<td></td>
</tr>
<tr>
<td>Foreign Invested Enterprises</td>
<td>0.53***</td>
<td>0.35***</td>
<td>-0.69***</td>
<td>0.09</td>
<td>446,663</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.12)</td>
<td></td>
</tr>
<tr>
<td>Private Enterprises</td>
<td>0.16***</td>
<td>0.09***</td>
<td>-0.75***</td>
<td>2.54***</td>
<td>1,153,886</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(0.53)</td>
<td></td>
</tr>
<tr>
<td><strong>Low Differentiation</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State-owned Enterprises</td>
<td>0.24***</td>
<td>0.13***</td>
<td>-0.71***</td>
<td>0.62*</td>
<td>360,688</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.35)</td>
<td></td>
</tr>
<tr>
<td>Foreign Invested Enterprises</td>
<td>0.47***</td>
<td>0.14***</td>
<td>-0.69***</td>
<td>0.24</td>
<td>607,071</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.00)</td>
<td>(0.28)</td>
<td></td>
</tr>
<tr>
<td>Private Enterprises</td>
<td>0.07***</td>
<td>0.02***</td>
<td>-0.67***</td>
<td>8.42**</td>
<td>1,856,290</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.00)</td>
<td>(3.34)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naïve Reg” column is estimated using specification (12). Estimation methods for the “Price Elasticity” and “Markup Elasticity” columns are the same as in previous tables. The “Naïve Reg.” column is estimated using specification (12). The “CMSE” column is estimated based on equations (10) and (11). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *. 

Panel of Table 33 cannot be attributed to a different typology of goods produced and exported across groups. Second, for each type of firm, results are consistent with our findings in section 4. Markup elasticities are higher for high differentiation goods than for low differentiation goods. Cross market supply elasticities are correspondingly lower for the former and higher for the latter group of goods.

To better appreciate the meaning and potential implications of our results for theory and policy, consider the response of different types of firms and products to an idiosyncratic appreciation of a foreign currency, say, the Mexican peso, relative to the renminbi. For private firms exporting goods with low differentiation, the depreciation of the renminbi leads to relatively high yet not complete pass through into the peso-denominated prices (1 - 0.07 = 93 percent, from row 9, column 4).
and a small (2%) increase in the markup. This small increase in the markup accounts for less than one third (0.02/0.07) of the change in export prices. In other words, Chinese private enterprises exporting low differentiation goods respond to an appreciation of the local currency by letting the local-currency price of their products fall and expanding their sales rather aggressively—adjustments to markups are minor. In our estimates, indeed, a 1% increase in the relative markup for the good in Mexico is met with an 8.4% increase in the relative quantity sold by the firm to Mexico (row 9, column (4) of table 33). For private firms exporting high differentiation goods, the exchange rate pass through into peso prices is somewhat lower, about 84% (1-.16). Yet, markup adjustment is not appreciably higher, 9% instead of 2%. Accounting for possibly different cost structures (due, for example, to the higher share of imported intermediate inputs in high differentiation goods), the strategic pricing behavior is quite comparable among private firms, regardless of whether they sell high or low differentiation goods.

Relative to private firms, for SOEs and FIEs pass through into import prices is considerably lower and markup adjustment is considerably higher. For high differentiation exports from China, ERPT into peso prices is around 50% (1-.46 = 54% for SOEs and 47% for FIEs, rows 4 and 5, column (1) of table 33). SOEs and FIEs clearly prefer to raise their markups, by 39% for SOEs and 35% for from FIEs (rows 4 and 5, column (2)), rather than expand sales. The estimated cross-market supply elasticities are indeed very small (0.38 for SOEs and 0.09 for FIEs). A similar picture emerges from our analysis of SOEs and FIEs exporting low differentiation goods, although, not surprisingly, markup adjustment is lower.

Overall, our results provide striking evidence that, on average, SOEs and FIEs exporting from China have significant market power in foreign markets, and exploit that power by letting their markups increase significantly with a foreign currency appreciation. This points to a strategic decision by firms to exploit market segmentation and keep destination markets separated: Averaged over all exported goods, there is only a 0.47% (SOEs) increase and no change for (FIEs) in the relative quantity sold in Mexico for a 1% increase in the relative markup. Conversely, over our sample period, private firms have aggressively pursued local market expansions.

A comment is in order concerning our findings. In comparison to FIEs and SOEs, private enterprises are on average smaller, reflecting the high rate of entry documented at the beginning of this section. Hence, a substantial share of them are likely at an early stage of their life cycle in which growth can be expected to have precedence over the exploitation market power. Interpreting our results from a cross-sectional perspective is likely to overestimate heterogeneity—once they achieve their equilibrium size, private firms may well exercise monopoly power and behave like FIEs and SOEs.

We leave to future research a refinement of our analysis along these lines.
E.3 Pricing behavior under the dollar-renminbi peg

The results discussed so far suggest that SOEs and FIEs wield substantial market power. Was this also the case in the first part of our sample, when the renminbi was pegged to the US dollar (2000-2005)? An analysis of pricing, markups and the CMSE during this period suggests a different story.

Our evidence for the dollar peg period is shown in Table (34). Across all types of firms in the table, adjustments of export prices to currency movements were modest—ERPT into foreign import prices was as high as 76 percent (1-0.24), 77 percent (1-0.23), and 88 percent (1-0.12) for SOEs, FIEs, and private firms, respectively (rows 1-3, column (1)).

Table 34: Pricing Strategies by Firm Registration Types (2000 – 2005)

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>High Differentiation</th>
<th>Low Differentiation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Price Elasticity</td>
<td>Markup Elasticity</td>
<td>Naive Reg.</td>
</tr>
<tr>
<td>State-owned Enterprises</td>
<td>0.24***</td>
<td>0.08***</td>
<td>-0.74***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>Foreign Invested Enterprises</td>
<td>0.23***</td>
<td>0.05**</td>
<td>-0.59***</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Private Enterprises</td>
<td>0.12***</td>
<td>0.09***</td>
<td>-0.76***</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.03)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

Note: Estimates based on the sample of multi-destination trade flows at the firm-product-time level to 154 destinations excluding Hong Kong and the United States. The “Naive Reg” column is estimated using specification (12). Estimation methods for the “Price Elasticity” and “Markup Elasticity” columns are the same as in previous tables. The “Naive Reg.” column is estimated using specification (12). The “CMSE” column is estimated based on equations (10) and (11). † indicates that the t-statistic of the bilateral exchange rate in the first stage is smaller than 2.58. Robust standard errors are reported in parentheses. Statistical significance at the 1, 5 and 10 percent level is indicated by ***, **, and *.

Both FIEs nor SOEs have smaller markup adjustments (rows 2 and 3, column (2)) in response
to exchange rates during the dollar peg era. Indeed, these firms appear to have been following a different strategy, namely, aggressively expanding quantity: a 1 percent increase in the relative markup in a destination is associated with a 3 percent increase in the relative quantity for SOEs and a roughly 8 percent increase for FIEs. In contrast to the managed floating period, private firms made significant markup adjustments of 9% (row 3, column (2)), the largest among all groups. We conjecture this is because the sunk cost for private firms to obtain an export license in China was relatively high in early 2000s. With only a limited number of private firms directly engaged in international trade, the level of competition among them was less severe. Consistent with our conjecture, we find a low cross market elasticity (2.26, row 3 column (4)) for this period relative to that during the managed float (4.72, row 3 column (4) in the previous table).

Important insights can be gained by looking at the second and third panels in the table, which break down our estimates by types of goods traded. Comparing SOEs exporting high and low differentiation goods (rows 4 and 7, column (2)), we see that the result in the first panel is entirely due to a significant markup elasticity for high differentiation products. For these products, around one-half of this incomplete pass through is due to markup adjustments (0.15/0.28, from row 4, columns (1) and (2)). For low differentiation exports by SOEs, we detect no markup adjustment (row 7, column (2)). The story is similar for FIEs: the average markup elasticity is 0.09 across all goods, but this is essentially driven by the high differentiation goods (with an elasticity of 0.10, row 5 column (2)).